5. Research Clustering, Income Disparities and the Growth of Regions in Europe

5.1. Analyzing Regional Disparities and Growth

Having explored spatial concentration, clustering and inter-regional co-patenting networks across Europe and the ERA in the former chapters 3 and 4, the following analysis will be shifted towards regional income disparities and regional growth.

Spatial income inequality (i.e., non-normal spatial distribution of income) is a phenomenon that determines the structure of both leading industrialized regions and regions in transition. According to Scott and Storper (2003), considering globalization as a simple spreading out of economic activity into a fluid "space of flows" seems to be a fundamental mistake. The analyses in the former chapters have already pointed out the persistence of clustering and geographic concentration of research activity across European regions. Thus, globalization is supposed to be accompanied by persistent agglomerative tendencies. As Scott and Storper (2003, 582) argued,

> "[i]n sum, large-scale agglomeration - and its counterpart, regional economic specialization - is a worldwide and historically persistent phenomenon that is identifying greatly at the present time as a consequence of the forces unleashed by globalization. This leads us to claim that national economic development today is likely not to be less but rather more tied up with processes of geographical concentration compared with the past."

With respect to the European regional development, it is especially important to analyze the spatial distribution of the gross domestic product (GDP) at the regional level. Although the European member countries seem to converge with respect to economic activity at the national level, several existing regional studies point to divergence and increasing within-subgroup inequality (Frenken and Hoekman, 2006; Paas and Schlitte, 2007; Crespo Cuaresma *et al.*, 2009b).[451] European enlargement activities have to deal with the issue of considerable income disparities within and between the European member states and their regions, as has already been discussed in the introductory chapter. Accordingly, there may be a crucial implication for the explicit target of regional convergence, especially at the regional level where several European policy tools are applied (e.g., NUTS2 and TL2/TL3) (OECD, 2003, 2006; European Commission, 2007c). The European Community's objective is to enhance economic and social cohesion and to achieve equity (Articles 2 and 4, and Title XVII of the Treaty establishing the European Community).[452]

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[451] See also Duro (2004), Combes and Overman (2004), Brülhart and Traeger (2005) and Combes *et al.* (2008).

[452] For a comprehensive review of the European structural policies refer to Rodríguez-Pose and Fratesi (2007) and European Commission (2011f) and European Commission (2011h).

The European Cohesion Policy and the objectives have their roots in Articles 2 and 4 and Title *XVII* of the Treaty of the European Community. According to Article 2, European cohesion policy should contribute to *"[p]romote economic and social progress as well as a high level of employment, and to achieve balanced and sustainable development."* Moreover, article 158 adds that *"[i]n particular, the Community aims to reduce the disparities between the levels of development of the different regions and the backwardness of the least favored regions or islands, including rural areas."* The European cohesion policy represents the second-largest item in the European Union's budget. The largest amount of European regional policy funding (over 80%) is applied to European regions that are falling under the European convergence objective. This policy objective generally focuses on NUTS2 regions. Financial support is given if regional per capita GDP is less than 75% of the EU-25 average (and, respectively, of the EU-27 average).[453] Box 5.1 summarizes key information about the European cohesion policy.

A strong motivation and solid argument for analyzing the structure and dynamics of European income distribution and European regional growth is based upon the fact that economic activity seems to show a persistent non-normal distribution as well as regional interdependence (Fotheringham *et al.*, 2002; Hauser *et al.*, 2008; Andersson and Gråsjö, 2009).[454] Regarding the OECD TL3 level, pan-European disparities and regional growth have not been very well studied so far. The majority of studies ignore variation at the level of smaller units as they are restricted to the NUTS1 or NUTS2 level (approximately 50-250 large aggregates) (Combes and Overman, 2004; Monfort, 2008). Therefore, one objective of the analysis in this chapter is to provide a systematic measurement of the distribution of economic activity and the regional components of inter- and intra-regional disparities of GDP per capita (PPP) over time and across the entire population of 819 European regions.

According to Maggioni and Uberti (2009), a crucial and worrying aspect of the European integration process is that the productive capacity agglomeration process, which emerges from market forces, may become too strong and may lead to social debates due to effects on wages, production, productivity and employment structures. There is evidence that countries that have experienced diverging regional income disparities tended to have, on average, higher national real GDP levels and growth rates, which is in line with the theoretical results of NEG models, as presented and discussed in chapter 2 (see sections 2.1.5.5 and 2.1.6.7).[455]

With respect to the European case, there is evidence that regions within the group of the 10 NMS are rather diverging compared with the EU-15 group of regions (Szörfi, 2007; Paas and Schlitte, 2008). Regarding cohesion, the core of European growth and the gravity center of future regional European cohesion policy is considered to have relocated to other parts of the European landscape of regions (see Box 5.1). The eastern enlargement process has induced an increase of about 30% of the European areal surface, an increase of more than 25% of the European population, but no significant increase in average per capita

[453] The NUTS2 level represents the level for structural cohesion policy. From an economic perspective, however, the NUTS2 level is problematic for several reasons (see also the discussion in chapter 3 and 4).
[454] See also Anselin (2007).
[455] See also Williamson (1965) and Baldwin and Martin (2004).

GDP (European Commission, 2003, 2004). Until the 1990s, the European regional growth poles were mainly concentrated in EU-15 metropolises, e.g., Munich, Berlin, Brussels, Vienna, Hamburg, Paris, Madrid, Milan, Rome. In the 1990s, new growth poles emerged in the capital towns and urban regions in Scandinavian countries, Spain, Ireland and recently in the NMS (Heidenreich, 1998). Moreover, it has been argued that economic growth and income is characterized by bi- or tri-modal distributions, originating from strong secondary growth poles (e.g., Naples, Barcelona, Stuttgart, Hamburg, Frankfurt in the EU-15). Nevertheless, the existing regional studies are mainly restricted to large macro regions (Abrham and Vosta, 2006; Melchior, 2008).[456]

This first part of chapter 5 analyzes income inequality dynamics. The analysis represents a pure quantitative approach that makes use of regional GDP per capita and population data. The section approaches the spatial inequality of per capita income for the period 1995 to 2006 by explicitly measuring the distribution and the structural dynamics across European regions (i.e., up to 819 TL3 regions). Several studies have shown that inequality increases with disaggregation from the macro to the micro level (Openshaw and Taylor, 1979). Therefore, the analysis decomposes the overall inequality/disparity (global spatial inequality) of GDP per capita (PPP) into a within-subgroup and between-subgroup component. Besides Gini computation, this study also applies generalized entropy measures. The analysis centers on EU-25 countries, but it also includes Switzerland and Norway, as they are geographically part of the European continent. Applying the statistical tools at the very disaggregated OECD TL3 level should help to depict spatial income disparities much better than using the European regional classification system (NUTS1/2-level), which is generally used for analyses of the European convergence objective. Moreover, the TL3 regions resemble functional regions and minimize potential spatial autocorrelation (see also chapter 4, section 4.2). The OECD definition should be aggregated enough to represent functional units.

In the first part of the chapter, the analysis tries to find empirical evidence for the following research questions: (i) Is GDP per capita still highly concentrated and unequally distributed within and between the European countries? (ii) Do the EU-15 countries show different patterns of regional disparity in terms of GDP per capita compared with the 10 NMS? (iii) Have regional disparities been persistent, decreasing or increasing since the 1990s? The analysis is related to the theoretical concepts and models on core-periphery structures reviewed in chapter 2, section 2.1, and contributes to the empirical studies presented in section 2.2.2.

Furthermore, besides the above-described inequality analysis at the level of European regions, the empirical analysis in the second part of this chapter also places emphasis on the question of whether patenting activity and the regional settlement structure do have a significant effect on regional growth and whether the EU-15 and the NMS regions show convergence of per capita income.

[456] Refer also to Heidenreich (1998) and Duro (2004).

Box 5.1: European Regional Policy

The European Fund for Regional Development (EFRD), the European Social Fund (ESF) and the Cohesion Fund (CF) are organized around three central objectives: (i) convergence, (ii) regional competitiveness and employment, and (iii) European territorial co-operation (European Commission, 2011g,f,h). The overall budget between 2007-2013 is Euro 347bn; Euro 201bn for the ERDF, Euro 76bn for the ESF, and Euro 70bn for the CF. The convergence objective is financially based on the ERDF, the ESF and the CF (European Commission, 2011g,f). The CF has been implemented in order to support European member countries whose gross national income per inhabitant is less than 90% of the EU average. The main target is to improve the economic and social conditions in backward member countries and to stabilize their economies (European Commission, 2011h). For the years 2007 to 2013, the CF is targeting Bulgaria, Cyprus, the Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia and Slovenia. Spain receives a phase-out fund if its GNI per inhabitant is less than the EU-15 average (national comparison) (European Commission, 2011g,e).
The ESF aims to improve European employment and job opportunities. The program intervenes in the framework of the convergence and regional employment and competitiveness objectives (European Commission, 2011g,f,h).
The ERDF is implemented to strengthen social and economic cohesion in the European Union by addressing imbalances between EU regions. Regarding the 2007-2013 funding program, the European Union's policy at the regional level is based upon three objectives: (i) convergence, (ii) regional competitiveness and employment, and (iii) European territorial co-operation. The three pillars replace the previous policy objectives of the period 2000-2006 (i.e., the antecedent *Objectives 1, 2 and 3*) (European Commission, 2011h).
The (regional) convergence objective covers those regions whose GDP per capita is below 75% of the regional EU average. Nearly all the regions of the NMS and many regions in Spain, Southern Italy, Greece, Portugal and in the New Laender (Germany) correspond to this criterion. The main priorities under the convergence objective are (i) human and physical capital, (ii) innovation output, (iii) the knowledge society, (iv) environment and (v) administrative efficiency. The budget allocated to the convergence objective is Euro 283bn (current prices). The past enlargement rounds (2004: 10 countries; 2007: 2 countries) have led to a decrease of the European average GDP per capita (section 5.3) (European Commission, 2011e). That being the case, several regions in the "old" EU-15 member states, which used to be authorized to receive funding under the convergence objective, are now beyond the 75% threshold level of the enlarged European Union. These regions can receive "phasing out" funding until the year 2013 (European Commission, 2011e).
The European Commission additionally advances European inter-regional co-operation in order to support European regions (and cities) in member states for joint programmes, projects and networks (European Commission, 2011d).

According to Barro and Sala-i-Martin (1991), among others, β-convergence is a necessary condition for σ-convergence, and usually the former process generates the latter. However, it is also possible for initially poor regions and countries to grow faster than initially rich ones, meaning that cross-sectional dispersion is either constant or increasing in the course of time (Barro and Sala-i-Martin, 2003; Hagemann, 2004). Since the famous cross-country studies of Baumol (1986), Abramovitz (1986), Barro (1991), Barro and Sala-i-Martin (1991), Barro and Sala-i-Martin (1992) and Mankiw *et al.* (1992), the convergence-divergence debate has also reached the level of regions (Abreu *et al.*, 2004, 2005; Harris, 2008).[457]

Barro and Sala-i-Martin (1991, 154) have analyzed a cross-section of 85 European regions for the period 1950-1985, and have found some kind of

> "[e]mpirical regularity that the rate of beta-convergence is roughly 2% a year in a variety of circumstances [...] the half-life of this convergence process is 35 years."

Moreover, Barro and Sala-i-Martin (2003, 496) concluded that

> "[t]he unconditional beta-convergence is the norm for these regional economies."

The existence and economic and political consequences of industry agglomerations, research clustering and spatial concentration of research in general are nowadays increasingly challenged. Furthermore, the issues of convergence and divergence are highly visible in the European policy agenda (Acs, 2002; Fujita and Krugman, 2003; Fujita and Mori, 2005).[458] The question is whether the initial income levels of poorer regions converge to the level of industrialized regions, which has some implications for regional growth paths and leads to normative conclusions.

According to the economic theories, convergence and/or divergence may occur depending on several structural factors. Neoclassical growth theory mainly argues for unconditional β-convergence due to decreasing returns of input factors (capital, labor) in the production function and homogeneous steady-state paths, whereas adherents to the endogenous growth theory and new economic geography argue for conditional convergence or even divergence (Martin and Ottaviano, 1999; Baldwin and Martin, 2004; Hagemann, 2004). The conditional convergence hypothesis is in general highly pessimistic with respect to homogeneous steady states. Absolute convergence to a unique steady state seems only plausible when analyzing within-country convergence; in this case, it is most likely to assume similar saving rates, technology bases, population growth, governmental policy, property rights and other conditions (Harris, 2008). In respect of between-country convergence, especially at the regional level, the units appear to have different steady-state paths (Solow, 2007; Brakman and van Marrewijk, 2008; Battisti and Vaio, 2008). However, the number of growth estimations at the regional level is still quite small compared with the overall number of cross-country studies at the national level. Regarding the origins of regional divergence, the spatial distribution of knowledge stocks and researchers is considered a crucial factor for regional development. Chapters 3 and 4 already demonstrated that the distribution of knowledge stocks (i.e., patenting activity) in Europe shows core-periphery structures. Persistent core-periphery structures in patenting activities should then be reflected in significant differences regarding regional growth rates (see sections 2.1.6.6 and 2.1.6.7), meaning that regions (and countries) exhibit divergence. This hypothesis will be tested in section 5.4.

The convergence-divergence hypothesis has been frequently tested by application of a σ-convergence measure. σ-convergence happens if the disparity of regional income levels

457 Baumol (1986) has used data for the period 1870-1978 to show convergence of productivity of sixteen industrialized countries.
458 Baldwin and Krugman (2001) and Fujita *et al.* (2001).

decreases in the course of time (Bräuninger and Niebuhr, 2005, 2008).[459] Further to this, β-convergence does not necessarily mean that regional inequalities are decreasing (Quah, 1993; Arbia *et al.*, 2005). Additionally, it has been shown in studies that spatial effects (i.e., spatial autocorrelation) have to be considered in regional convergence analyses, especially when large spatial aggregates are used (Dewhurst and McCann, 2007). Neglecting spatial effects between regions would reduce regions to isolated islands in a non-interdependent space (Paas and Schlitte, 2008).[460] Nevertheless, some studies already reported that the implementation of national and regional controls might reduce spatial dependence (Bräuninger and Niebuhr, 2005; Geppert and Stephan, 2008).[461]

From an empirical perspective, the determinants of regional growth and income disparities in Europe have received increasing attention in recent years (Harris, 2008; Geppert and Stephan, 2008; Petrakos and Artelaris, 2009).[462] Box 5.2 offers a short overview of regional studies.[463]

The great majority of authors restricted their research efforts on the level of administratively defined macro regions, which sometimes consist of spatial units representing the nation state (e.g., Cyprus, Denmark, Estonia, Latvia, Lithuania, Luxembourg, Malta and Slovenia). It is obvious that such classifications are by definition not suited for an analysis of regional settlement structures, agglomeration economies, commuting effects and various forms of spatial spillovers (Brakman *et al.*, 2005). Moreover, several researchers followed the predefined NUTS classification, although empirical evidence has suggested that the NUTS2 level is inferior for many reasons. The perhaps most serious issue is that spatial dependence is present in most NUTS1/2 regressions; the autocorrelation of dependent variables and covariates appears as a result of the averaging process in the context of data aggregation.[464] In general, the averaging process via spatial aggregation is considered to reduce the variance within the population of spatial units (Dewhurst and McCann, 2007).

459 See also Durlauf and Quah (1999), Niebuhr and Schlitte (2004) and Paas *et al.* (2007).

460 See also Quah (1996), Rey and Montouri (1999) and Le Gallo and Dall'erba (2003).

461 Ezcurra *et al.* (2007, 403), among others, recently explained their decision to rely on NUTS2 units as follows: *"It should be noted, however, that, as in any analysis of spatial data involving different geographical units, our results may be sensitive to the level of territorial disaggregation adopted (see Ertur et al. (2006) for further details on this issue). In any event, it is worth mentioning that our decision to work with NUTS-2 regions is justifiable in terms of European regional policy considerations. In fact, this is the spatial level at which eligibility under Objective 1 of Structural Funds is determined since the reform of the European regional policy in 1989."*

462 See also Duro (2004) and Arbia *et al.* (2005).

463 For an extended overview see Baumont *et al.* (2003), Le Gallo and Dall'erba (2003), Magrini (2004), Niebuhr and Schlitte (2004), Abreu *et al.* (2005), Fischer and Stirböck (2006), Feldkircher (2006), Frenken and Hoekman (2006), Paas and Schlitte (2008), Battisti and Vaio (2008), Petrakos and Artelaris (2009), Crespo Cuaresma *et al.* (2009a), Crespo Cuaresma *et al.* (2009b) and Crespo Cuaresma *et al.* (2010).

464 Refer also to chapter 4, section 4.2 for more details.

Box 5.2: Regional Growth Studies - A Short Overview

The majority of existing regional studies have examined the European growth process at an aggregated spatial level (large regional administrative units), e.g., at the NUTS1/NUTS2 level (Magrini, 2004; OECD, 2009a). Studies in this line are, among others: Baumont *et al.* (2002) (138 NUTS2 regions, 1980-1995); Feldkircher (2006) (246 NUTS2 regions, 1995-2002); Bräuninger and Niebuhr (2005) (192 NUTS2 regions, 1980-2002); Debarsy and Ertur (2006) (237 NUTS2 regions, 1993-2002); Brakman and van Marrewijk (2008) (257 NUTS2 regions, 1995-2005); Brülhart and Traeger (2005) (236 NUTS2 regions, 1975-2000); Fischer and Stirböck (2006) (256 NUTS2 regions, 1995-2000); Petrakos *et al.* (2007) (249 NUTS2 regions, 1990-2003); Crespo Cuaresma *et al.* (2009b) (255 NUTS2 regions, 1995-2005); Martin (2001) (195 NUTS regions, 1975-1998); Rodríguez-Pose and Fratesi (2004) (195 regions, 1988-1999); Ezcurra *et al.* (2007) (197 NUTS2 regions, 1977-1999).
It is obvious that all listed studies are conceptualized at the more aggregated NUTS1/2 level, which enforces spatial dependence in regressions due to data averaging via the aggregation process. Moreover, the majority of studies are based on the "Cambridge Econometrics regional database", which represents a workhorse database in European growth-convergence studies at the NUTS1/2 level.

The studies of Niebuhr (2001), Christopoulos and Tsionas (2004) and Dall'Erba (2005), among a few others, are restricted on within-country growth patterns for selected countries at the much smaller NUTS3 level, which is, however, closest to the theoretical ideas and empirical issues related to agglomeration economies, clustering and proximity effects (see chapter 2). In this respect, it seems essential to note that the approach applied in this study is different to the large fraction of existing studies as it uses a different spatial classification system, including regions at a smaller level than the common NUTS2 level. Accordingly, the only quantitative studies, to the author's knowledge, which analyzed the convergence issue at a smaller level than the NUTS2 level, for the EU-15 group, the NMS and the enlarged group of the EU-25, have been conducted by Frenken and Hoekman (2006), Paas and Schlitte (2007), Falk and Sinabell (2008) and Petrakos and Artelaris (2009).[465]

To sum up, it can be concluded that (i) most studies are accomplished at the aggregated level of administrative NUTS2 units but not at a more disaggregated regional level, which is mainly a result of data limitations and an unbalanced NUTS3 classification; (ii) empirical evidence on the different linkages between regional growth, spatial spillovers and especially the role of regional typologies, regional disparities and research activity are still scarce at the level of European regional classifications below NUTS2. Following theoretical models in the new economic geography and growth tradition, regional income disparities and divergence phenomena are foremost reflections of spatial distributions, i.e., the co-location and co-agglomeration of agents, technology fields, production factors and markets. Moreover, these disparities can be based upon different spillover effects from neighboring regions as has been theoretically discussed in chapter 2 (Martin and Ottaviano, 1999, 2001; Fujita and Thisse, 2003; Baldwin and Martin, 2004).

[465] Similarly, Le Gallo and Dall'erba (2003), Fischer and Stirböck (2006), Ertur and Koch (2006), Feldkircher (2006) and Crespo Cuaresma *et al.* (2010), among a few others, have analyzed the European convergence process of GDP per capita in the light of spatial models that account for spatial spillovers and/or spatial regimes.

The growth analysis in the second part of chapter 5 tries to find empirical evidence for the following open research questions: (i) Are European regions and their sub-groups converging to different steady-state paths according to the conditional convergence theory? (ii) Are the regional growth rates of GDP per capita affected by inter-regional spillovers at a proximate distance? (iii) Do urban areas and metropolitan and capital regions exhibit higher growth rates compared to rural regions? (iv) Is the regional research density, i.e., the patenting activity, significant and positive in regional growth regressions? (v) Do the NMS show differing growth paths vis-à-vis the EU-15 group? The growth regressions are related to the theoretical concepts and models on core-periphery structures reviewed in chapter 2, with special emphasis on regional growth (section 2.1), and contribute to the empirical studies presented in section 2.2.2.

From an empirical point of view, the following empirical analysis applies cross-sectional unconditional and conditional β-convergence estimations/ growth regressions for European TL3 regions. Since spatial dependence could play a role in regional data, the analysis incorporates spatial econometric techniques. Dummy variables for the regional typology are additionally introduced into the growth regressions, i.e., urban, intermediate and rural regions, and metro and capital regions, in order to control for the level of urbanization and for the population density, the population size, and the size of the local market, respectively. Due to the MAUP, the econometric results may differ from the aforementioned growth/ convergence studies. Unfortunately, several causalities, mechanisms and factors cannot be analyzed because of the very limited availability of additional data in the context of more than 800 European regions. Accordingly, due to the chosen research methodology and the large number of regions, the empirical analysis has to abstract from place-specific factors and path dependencies (i.e., formal and informal institutions, culture, place-specific history, first-nature geography, epistemic communities, regional policy).

The remainder of chapter 5 is as follows. The underlying database is described in section 5.2. The first empirical part in section 5.3 analyzes income inequality dynamics. Descriptive statistics and the results of the global income inequality/disparity analysis are presented and discussed. The results of within- and between-subgroup income inequality decomposition at the level of European regions are demonstrated in section 5.3.3. The second part of the chapter presents and discusses growth regressions for European regions (section 5.4). After a short introduction to growth estimations in section 5.4.1, the results from the unconditional convergence estimations are presented and discussed in section 5.4.2. Afterwards, conditional growth regressions for the NMS and EU-15 regions are discussed in section 5.4.3. In section 5.4.4, the regression set-up is extended to conditional spatial regression models.[466]

[466] Disparity/ inequality measures have been performed with STATA 11; growth regressions in this chapter have been run with STATA 11, OpenGeoDA and ArcGIS 9.3.1.

5.2. The Database: Regions, Patents and the Settlement Structure

One severe issue with empirical investigations of core-periphery structures, spatial dynamics and geographic concentration is the question of aggregation from a sectoral and spatial perspective (see also chapter 3). Geographical economics always suffers from the issue of defining and defending the correct and meaningful industrial and geographical scale of analysis (Audretsch and Feldman, 1996; Brakman *et al.*, 2005). The same issue exists for technology correspondence tables. Brakman *et al.* (2005) argued that industries and regions correspond to their theoretical counterparts and that there is a tradeoff between industrial and regional detail. Some scholars address 36 manufacturing industries (NACE, SIC) which are available at the NUTS0 level (national level); other scholars, instead, prefer smaller levels, e.g., 17 industries, which exist at more disaggregated spatial levels. Therefore, a serious problem in geographical economics and the geography of innovation literature is the definition and usage of spatial units (see chapter 3).[467] Brakman *et al.* (2005, 7) recently suggested that

> "[t]he geographical scope of the NEG is by and large restricted to sets of NUTS3 regions. This suggests that there is something to gain from sacrificing some industrial detail for the sake of regional detail."

The underlying database in this chapter includes raw data extractions for 819 TL3 regions (see table B.3, appendix).[468] The regional cross-sectional population consists of the TL3 regions within the EU-25 member states and Norway and Switzerland (OECD, 2003, 2006). Thus, the population in this study covers 774 TL3 micro regions, which form the EU-25 member states; additionally, 45 TL3 units from Norway (19 TL3) and Switzerland (26 TL3) are included. From the 774 regions, 651 represent the EU-15 and 123 belong to the NMS. Switzerland is included to avoid black holes in the spatial structure. However, Norway is eliminated from the regressions for several reasons. Moreover, Croatia, Romania and Liechtenstein are abandoned due to data constraints. Additionally, Luxembourg and Cyprus are excluded from the inequality decomposition. Finally, the French and Portuguese overseas regions (islands) as well as Spanish Atlantic islands are excluded from the growth regressions.

[467] The geographical scope of the NEG literature is, according to Brakman *et al.* (2005), by and large restricted to empirical analyses at the NUTS2 and NUTS3 level.

[468] The only difference between the TL3 and NUTS3 in this study results from aggregating the 439 "Stadt- / Landkreise" in Germany (NUTS3) to 97 so called "Raumordnungsregionen" (planning regions) and aggregating Dutch and Belgian NUTS3 units to the NUTS2 level (which is OECD TL3). Similarly, Greek islands and small units are aggregated to Greek NUTS2 units and solve several issues. (i) Several NUTS3 units are relatively small and numerous in comparison with other EU NUTS3 units. The application of, e.g., 439 German NUTS3 regions would increase the influence of German regions in the analysis as they account for one-third of all NUTS3 observations (see also Magrini, 2004). (ii) Additionally, when using NUTS3 GDP data, the existence of relatively small regional units may induce the issue of commuting of workers between their place of residence and place of work and thus mean biased GDP measures (e.g., Berlin, London, Paris).

The study uses purchasing power (PPP) adjusted GDP per capita data as dependent variable in the regression (Monfort, 2008).[469]

The majority of existing regional studies on the enlarged European Union and the ERA primarily analyze the larger administrative NUTS2 units.[470] Frenken and Hoekman (2006) concluded that the NUTS2 level, which has been applied in the majority of convergence and inequality studies, is poorly defined in terms of regional typologies, as large NUTS2 regions contain urban centers and rural regions at the same time, which means that the administrative spatial classification system largely differs from the real functional boundaries of regions. Similarly, Abreu *et al.* (2005, 34) concluded that

> "[a]ggregating several smaller units into larger ones makes matters worse, since it averages out the variation in the variables of interest (the modifiable areal unit problem). One solution may be to redefine boundaries of the spatial units from scratch, using highly disaggregated data and Geographical Information Systems. [...] the level of aggregation should be chosen according to the theoretical model under consideration."

Therefore, studies on spatial disparities, agglomeration economies and research clustering at the NUTS2 level are problematic as spatial variation generally disappears due to aggregation (and averaging) (Arbia and Petrarca, 2010).[471] Taking all these concerns into account, it has to be argued that the OECD TL3 level (OECD, 2003, 2006) fits best to the proposed research questions and the theoretical background (see chapter 2), because the TL3 level gives the opportunity to test the hypothesis of growth disparities between capital regions, urban areas and rural regions. Moreover, it represents an established regional classification system which enables future comparisons with other studies.

5.3. The Development of Income Disparities in Europe

5.3.1. A Descriptive Overview

Analyzing regional income distribution across the 819 TL3 regions of the enlarged European Union (including Switzerland and Norway) shows remarkable regional disparities between the NMS and the EU-15; but also within the EU-15 and NMS groups. The analysis places the emphasis on the distribution of GDP per capita in purchasing power standards (PPP), where income is adjusted for price level differences across countries.

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469 Generally, PPP corrected data are adjusted for differences in national price levels but they do not consider within-country price differences, although there might exist considerable regional differences. GDP data at the TL3 level have been collected, and if necessary, calculated and/or transformed for the period 1995 to 2006; e.g., Switzerland and Norway.

470 To the author's knowledge, Frenken and Hoekman (2006), Paas and Schlitte (2008) and Melchior (2008), among a few other studies, contributed with a similarly detailed spatial classifications system.

471 Arbia and Petrarca (2010, 10) concluded that *"[t]he efficiency loss connatural to aggregation is, generally speaking, mitigated by the presence of a positive spatial correlation parameter and conversely exacerbated by the presence of a negative spatial correlation parameter. This result is coherent with the theoretical expectation. Positive spatial correlation implies that we aggregate between similar values thus preserving variability."* See also Abreu *et al.* (2005) and Burger *et al.* (2008).

A first descriptive analysis shows that there exists (i) a core-periphery structure with relatively high income levels in the center of the European Union and (ii) relatively low levels of GDP per capita in peripheral areas and regions at the borderline of the enlarged European Union. Figures 5.1 and 5.2 highlight the development of regional per capita income (PPP) in Europe between 1995 and 2006 in maps.[472] European regions widely differ by means of the spatial distribution of per capita income and thus show strong regional disparities. Moreover, it is clearly visible that the enlarged European Union (EU-25, CH, NO) also yields country-specific income levels, meaning that regions only differ to some degree from their national average. Thus, variance seems to be rather modest within countries, compared to the between-country differences in the early years.

The first map (figure 5.1) displays the distribution of regional per capita income relative to the EU-27 average in the year 1995 (including Switzerland and Norway). The illustrated distribution of regional GDP per capita differentiates the more successful regions of Europe, which are located in the core of Europe, from the more backward and underdeveloped ones. The high-income regions form a functional area that is commonly known as the European "blue banana" (Heidenreich, 1998; Martin, 1998b; Maggioni *et al.*, 2007). Accordingly, most of the relatively rich regions belong to the northern part of the European continent, including Northern Italy, Southern Germany, Southeast France, Ile-de-France, the southern regions of Great Britain, Belgian regions and Dutch regions, among others. Low income regions, with a GDP level below 75% of the EU-27 average, can be found in the eastern part of Germany, in Greece, in Southern Italy, in Ireland and in the Western parts of Spain and Portugal (at least in the 1990s). Moreover, it is argued that areas accompanied with high levels of GDP per capita are often those that are hosting the capital cities. Furthermore, metropolises and capital regions represent the locations of diversified high-technology industries and service sectors (see chapter 3, section 3.5); e.g., Southern Ireland (Dublin), Denmark (Copenhagen), Germany (Berlin, Stuttgart, Frankfurt), France (Paris), the UK (London), Southern Finland (Helsinki), or the Southeast of Sweden (Stockholm). Within low performing EU countries, capital regions are identified to serve as "growth poles" since the 1990s, e.g., Lisbon, Madrid, Prague or Warsaw (see also OECD, 2009a,b).[473]

The second map (figure 5.2) visualizes European regional per capita income levels for the year 2006. Very high income levels can be observed in the southern parts of Ireland, in the eastern regions of Spain and Southern UK areas, whereas other regions in the mentioned countries are still lagging behind. A remarkable north-south gradient is still present in Italy. In addition, the map seems to support the hypothesis, that particularly metropolitan regions and/or capital regions show relatively higher per capita income levels compared to the European average, similarly to the 1990s.[474]

[472] See figure A.47 in the appendix for the visualization of the regional GDP per capita distribution in the year 2000.

[473] The second map (figure A.47, appendix) illustrates regional GDP per capita (PPP) for the year 2000. Very low levels of per capita income exist in, e.g., Western regions of Spain and Portugal, Southern Italy and some Northern areas in the United Kingdom. Similarly, the Greek regions and some of the New German Laender still suffer from relatively low income levels. Moreover, most parts of Ireland have developed above the European average since the year 1995 in terms of regional GDP per capita.

[474] This hypothesis will be additionally challenged in the second part of this chapter (see section 5.4).

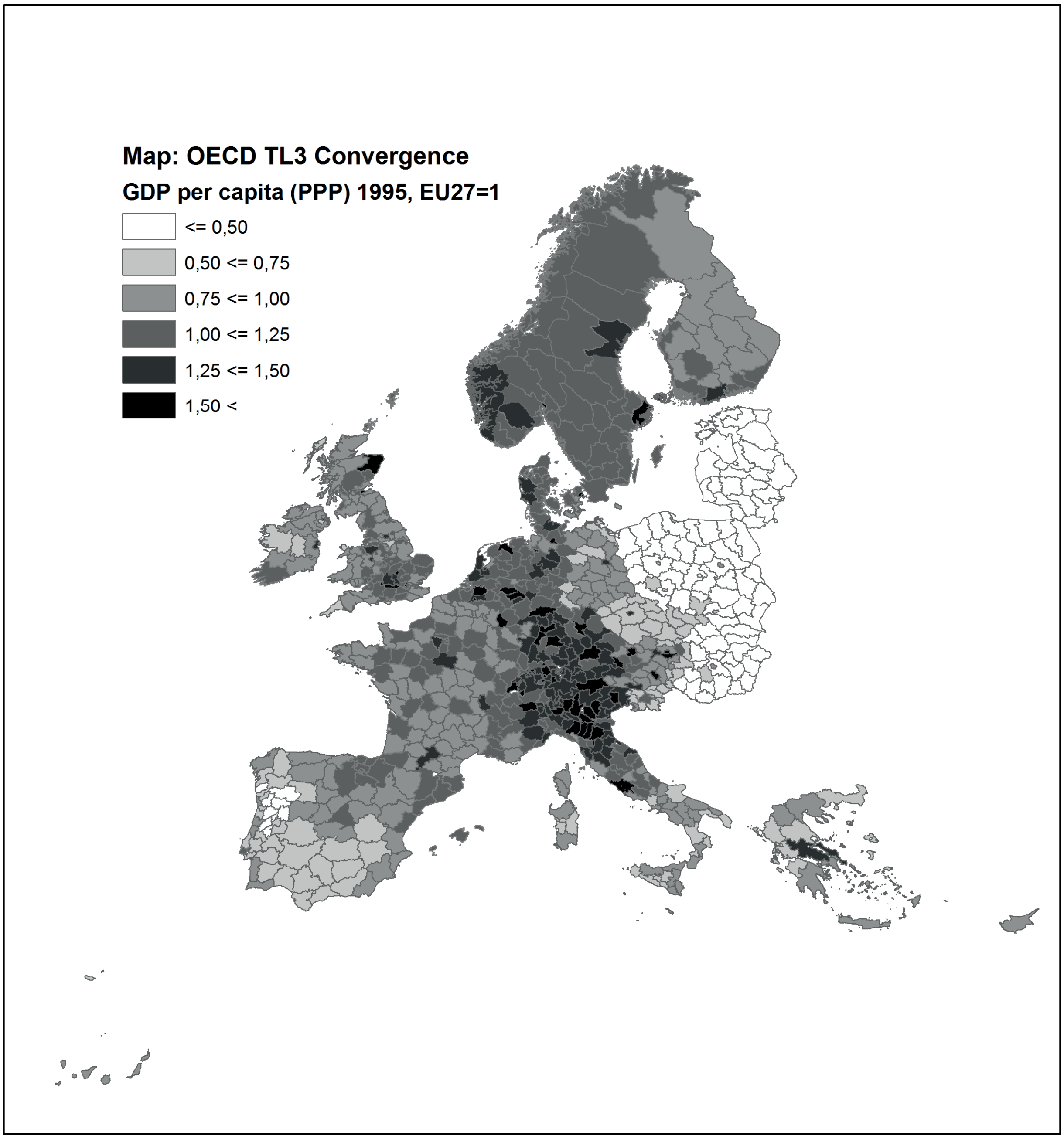


Fig. 5.1. GDP per capita (PPP) year 1995
Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

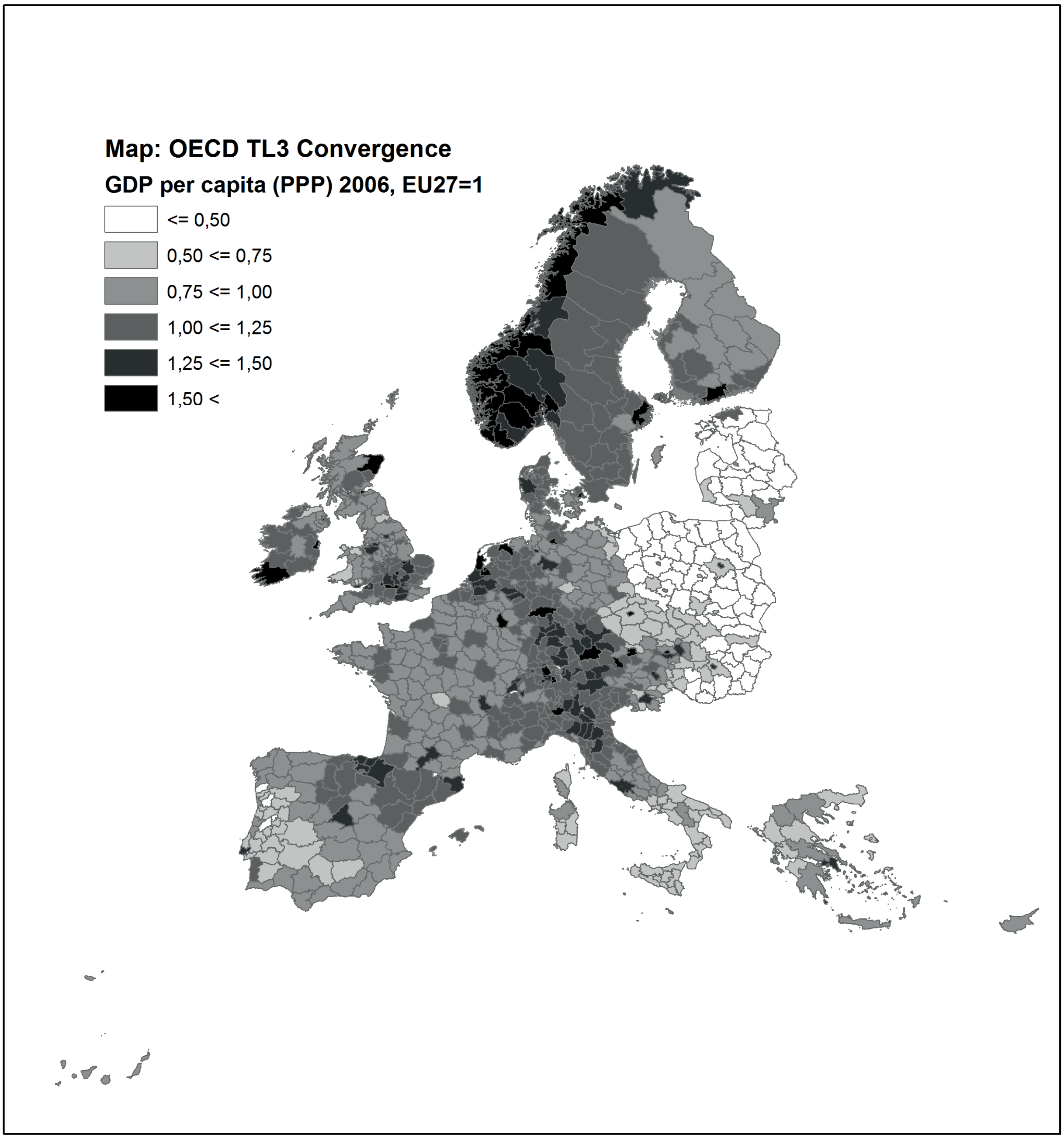


Fig. 5.2. GDP per capita (PPP) year 2006
Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

The third map (figure 5.3) highlights the GDP per capita (PPP) growth rates of all 819 European regions between 1995 and 2006, expressed in relation to the EU-27 average. Comparing the regional GDP per capita growth rates of European regions shows again a north-south and east-west gradient that has already been identified in the research clustering study in chapters 3 and 4. Nevertheless, almost all eastern and southern European regions are characterized by higher GDP growth rates, compared to European core regions. The map seems to support the well-known hypothesis that per capita growth between 1995 and 2006 was, on average, higher in the peripheral and economically backward regions of Europe. This hypothesis originates from the well-known and well-described catching-up theory, i.e., β-convergence concept, that is based on the canonical neoclassical growth model (Solow, 2007) and the related discussion on social capabilities and additional factors that determine regional (and national) development (Abramovitz, 1986; Barro and Sala-i-Martin, 1991; Harris, 2008). High growth rates, above the EU-27 average, can be observed in, e.g., Ireland, Spain, the NMS, the northern part of Greece and Portugal. Besides this development, medium-high growth rates are observable within the so-called "blue banana" (mainly high-growing regions of the EU-15), e.g., Dutch regions, Southern UK and several central European regions such as Milan, Munich, Stuttgart, Noord-Brabant or Düsseldorf.[475] Accordingly, it can be argued that there is something to gain from a closer look at the regional typology and at the development within the NMS group.

The box plots (see graphs in figure 5.4) depict that the development of European countries' average growth rates depend on the growth rates of a few leading regions, which have also reached a much higher level of GDP per capita compared to the national average. These are typically capital regions, metropolises and urban regions. Some of them serve as secondary growth poles (see also Williamson, 1965; Arbia *et al.*, 2005; Szörfi, 2007). Such high-growing capital regions are located in Hungary, Estonia, Poland, the Czech Republic, Latvia, Lithuania, Slovenia and Slovakia. The box plots show the inter-quartile distances and the lower and upper quartiles for the EU-15 and NMS countries for several years (1995 and 2006). Besides the structure in the year 1995, the figure also highlights the year 2006 and the average yearly growth rates for the EU regions. It is evident that the 0.25 quartile has increased in almost all countries between 1995 and 2006, which means that the lower tail of the income distribution has increased in absolute terms. Besides the quartiles and the inter-quartile distances, the study also analyzes if regions with initially high levels of GDP per capita (PPP) in 1995 suffer from very low average yearly growth rates, which would be in line with the canonical neoclassical convergence approach and the assumed decreasing returns and lower growth rates near the unique steady-state (see also section 5.4).

National Gini coefficients and a decomposition of overall regional income disparities (GDP per capita) into within- and between-subgroup components are performed in the following analysis in order to gain more information about the spatial structures of the growth process. Finally, the aforementioned picture of catching-up regions is additionally highlighted by distribution functions (kernel density) in figure 5.5. Three groups of regions are illustrated: (a) the EU-25 and Switzerland and Norway, (b) the EU-15 and (c) the NMS. It is obvious from the graphs that the distribution of the EU-25 group (with Switzerland and Norway) has changed between 1995 and 2006 due to remarkable shifts in the lower

[475] For similar results at a higher aggregation level see OECD (2009a,b).

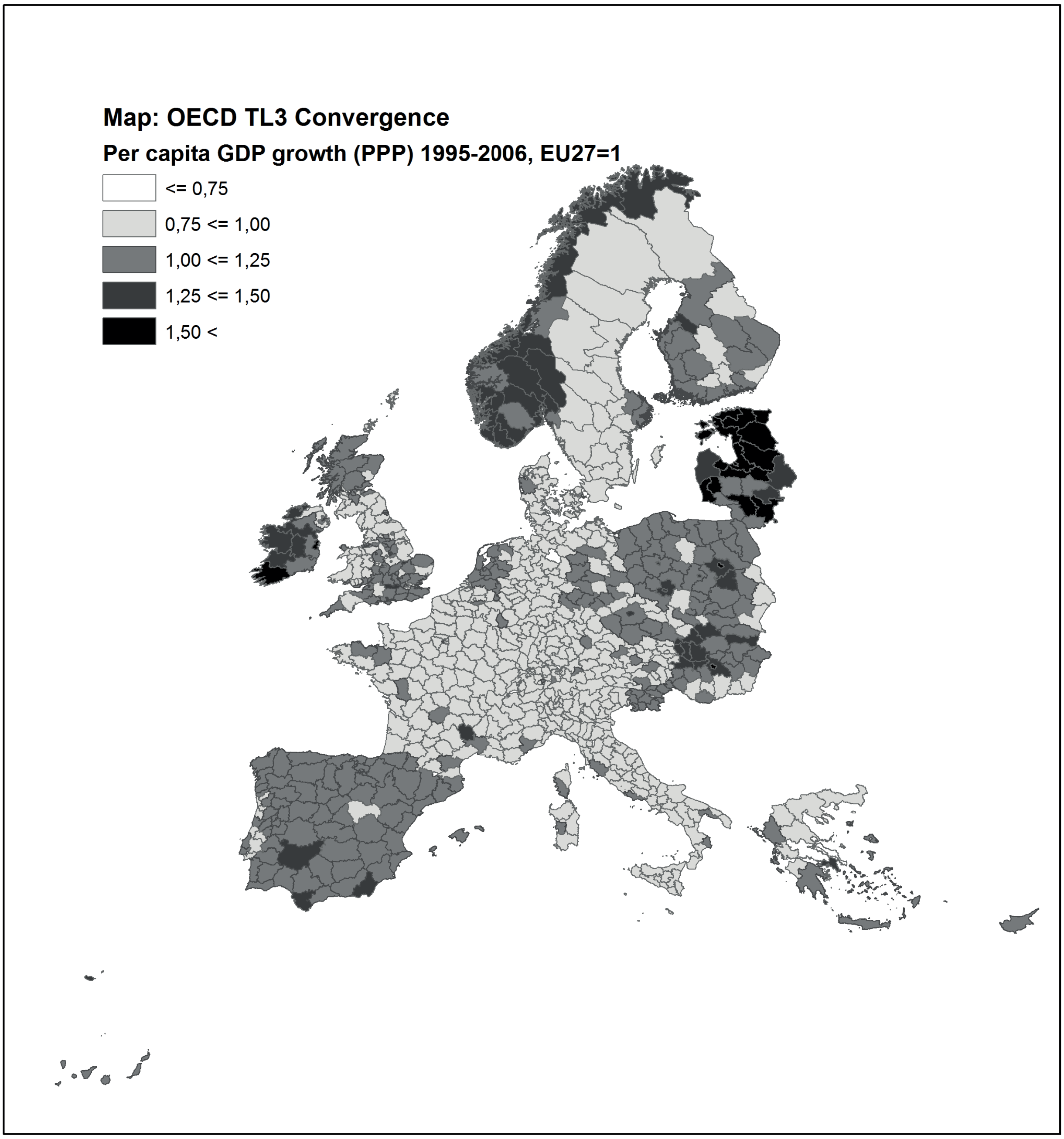


Fig. 5.3. Growth Rates of GDP per capita (PPP) 1995-2006
Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

tail of the income distribution, i.e., a catching-up process of several poor regions (see also Geppert and Stephan, 2008).

5.3.2. Measures of Concentration, Disparity and Inequality

5.3.2.1. Regional Disparities and the Gini Coefficient

After the introductory analyses and data presentation in the previous section, the following analysis addresses the distributional characteristics and regional disparities of GDP per capita by means of quantitative methods. Geographic concentration and regional disparities are a general phenomenon in regional economics (Hinloopen and van Marrewijk, 2004; Arbia *et al.*, 2005).

Furthermore, concentration (disparity) measures are assessed in a similar manner compared to specialization. The sole difference to specialization measures is that instead of a comparison of industrial structures within a single region, concentration measures involve a comparison of regions' industrial structures in the context of a larger spatial aggregate (Krugman, 1991; Ellison and Glaeser, 1997).[476] According to the aforementioned issues, the literature on geographic concentration and spatial inequality has developed some common empirical measures and indices. Regional disparities can be measured by application of various indices. The most common statistical approaches are the Herfindahl-/ Herfindahl-Hirschman index, the location quotient (Hoover-Balassa index), the Gini coefficient, the Krugman index, Theil's T and Theil's L index, and modifications of the generalized entropy index (Litzenberger, 2007; Monfort, 2008; Jenkins and Kerm, 2009).[477] Some of these indices have been already presented and discussed in chapter 3.

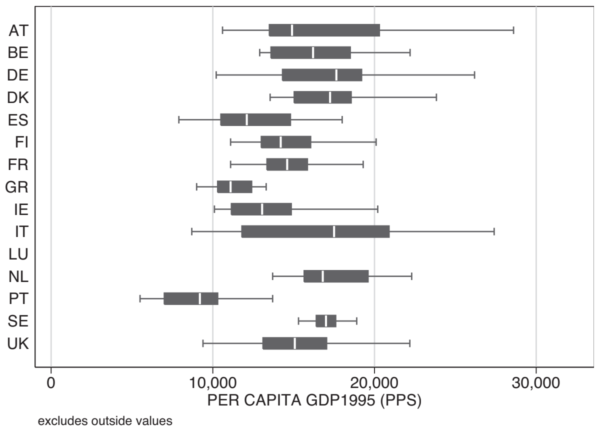
However, disparity or inequality indices should satisfy several axioms (Jenkins and Kerm, 2009).[478] For measuring overall disparity (inequality), the study makes use of the locational Gini coefficient and the generalized entropy measure (i.e., the Theil and Atkinson index). Generally, the Gini coefficient (see also chapter 3, section 3.4), which is applied in the following analysis, is a measure of statistical disparity or inequality. According to the traditional methodology, studies commonly used the Gini coefficient as a measure of inequality of income or wealth (Dewhurst and McCann, 2007; Jenkins and Kerm, 2009). The Gini coefficient is defined mathematically based on the Lorenz curve concept. However, in the context of regional disparities, Gini computations at the level of regions have to include weights for the treatment of spatial heterogeneity (e.g., population, surface). In this respect, relative shares for each subspace are computed with $g_j = [s_j/y_j]$; with s_j being the GDP share of region j and y_j being the population share of the region.[479] Equation

[476] See Amiti (1997), Amiti (1999), Laursen (1998), Midelfart-Knarvik *et al.* (2000) and Jenkins and Kerm (2009) for further details.

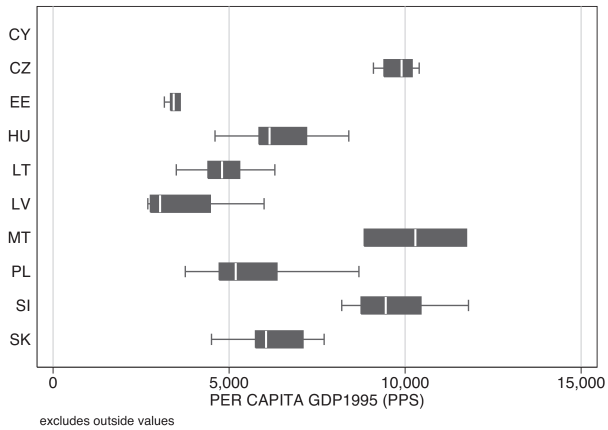
[477] See also Kim (1995), Amiti (1999), Keilbach (2000), Aiginger and Pfaffermayr (2004), Combes and Overman (2004).

[478] See also section 3.4. For further details see Cowell (1995).

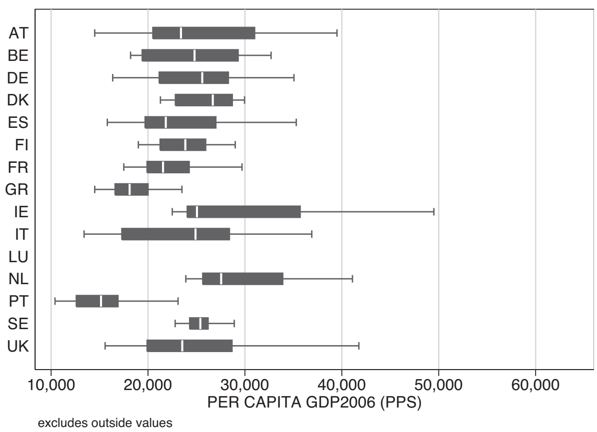
[479] It should be noted that the obtained Gini from g_j is identical to the usage of GDP per capita of region j divided by the GDP per capita of the aggregate of regions $\sum_j$.



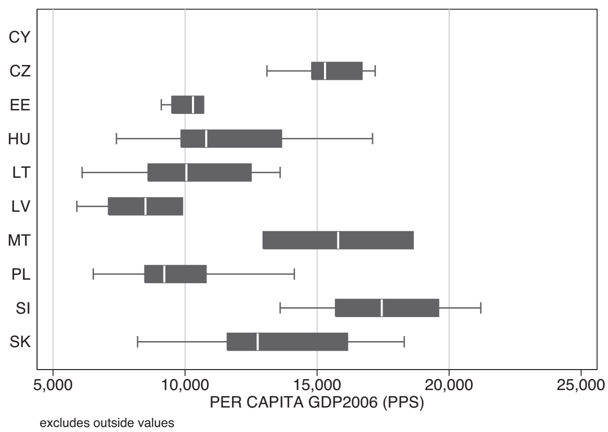
(a) EU-15 GDP per capita (PPP) in 1995



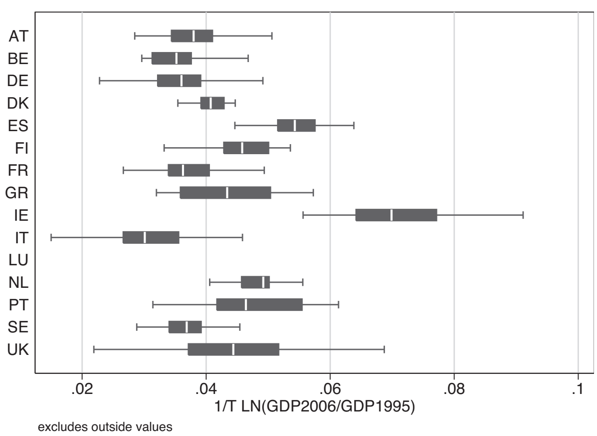
(b) NMS GDP per capita (PPP) in 1995



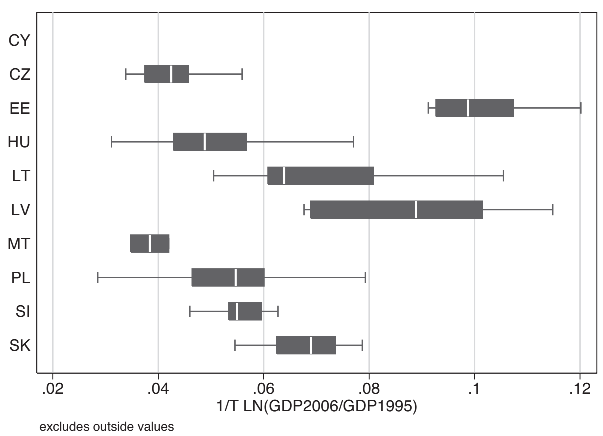
(c) EU-15 GDP per capita (PPP) in 2006



(d) NMS GDP per capita (PPP) in 2006

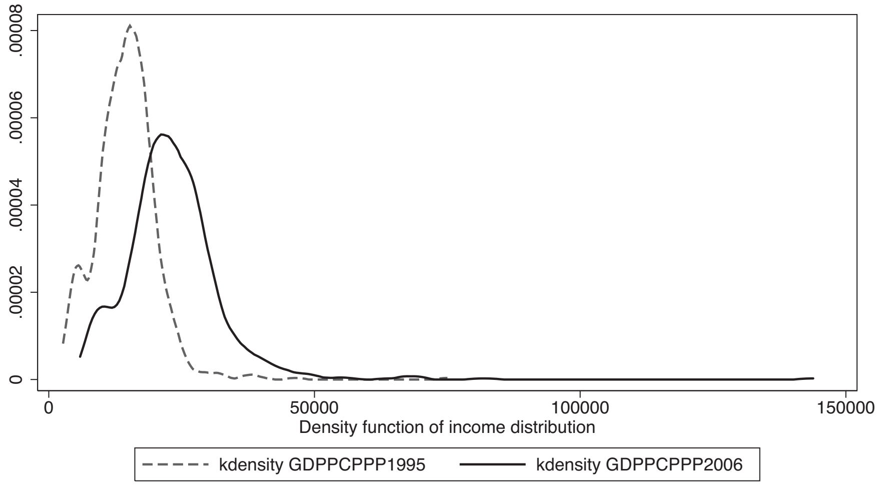


(e) EU-15 GDP per capita (PPP) Growth Rates 1995-2006

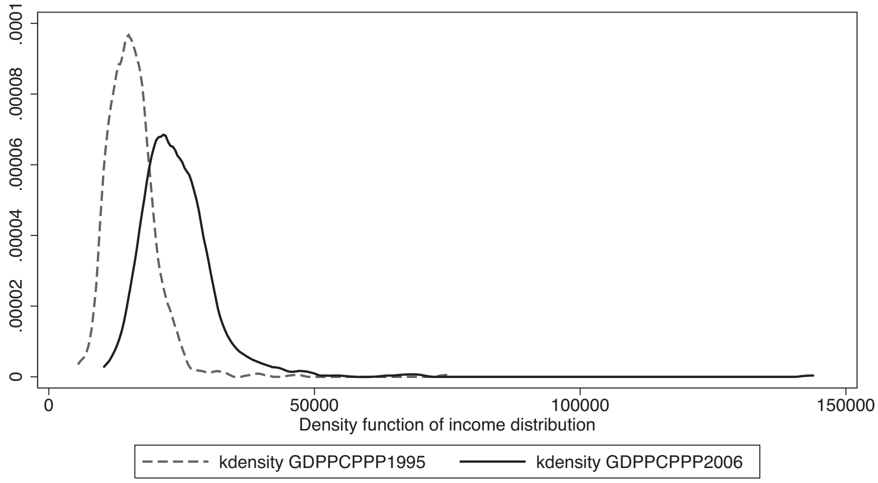


(f) NMS GDP per capita (PPP) Growth Rates 1995-2006

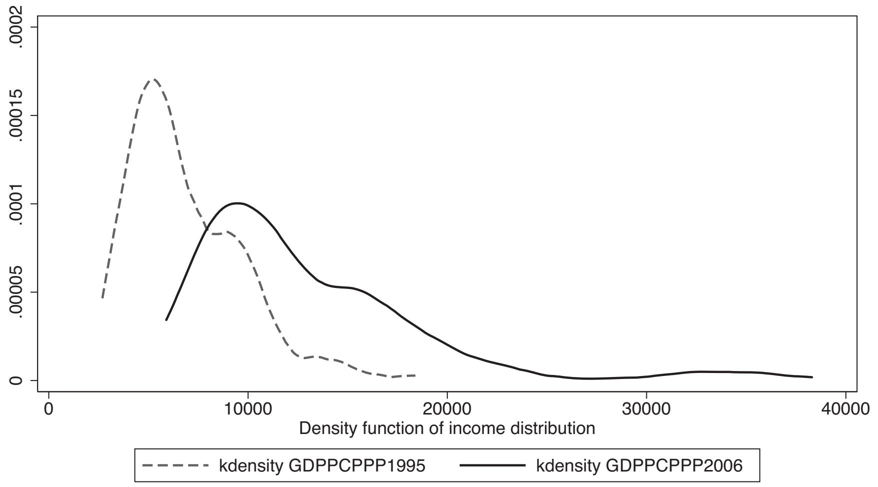
Fig. 5.4. Boxplot: GDP per capita (PPP) level vs. growth rate
Source: own calculations and illustration.



(a) Kernel density GDP (PPP) per capita, regions in the EU-25, CH, NO (1995 vs. 2006)



(b) Kernel density GDP (PPP) per capita, EU-15 regions (1995 vs. 2006)



(c) Kernel density GDP (PPP) per capita, NMS regions (1995 vs. 2006)

Fig. 5.5. Kernel density: density function of income distribution TL3 regions by group
Source: own calculations and illustration.

5.3.1 represents the locational Gini as has been already introduced, discussed and applied in chapter 3 (see section 3.4).

$$G^*_{LOC} = \left[2\left[\frac{1}{2} - \left[\sum_{j=1}^{n}\left(\frac{1}{2}y_j s_j\right) + \sum_{j=1}^{n}\left(y_j \sum_{k=j+1}^{n} s_k\right)\right]\right]\right]\left[\frac{1}{1-miny_j}\right] \qquad (5.3.1)$$

G^*_{LOC} is a population weighted Gini coefficient in terms of y_j, which needs a normalization procedure. Normalization is accomplished by correcting for the minimum populated European region (with $min(y_j)$), which guarantees a maximum concentration surface as presented in equation 5.3.1. In case that the regional share of GDP, s_j, across subspaces j is identical to the share of the reference distribution, y_j, we observe an equal distribution and no disparity (i.e., $g_j = 1$ and $G^*_{LOC} = 0$). The Lorenz curve is then identical to the bisecting line. However, the more the distribution of the economic activity under analysis, s_j, differs from the reference distribution, y_j, the larger is G^*_{LOC}. In this respect, G^*_{LOC} takes s_j and y_j for each region and computes the cumulated sum of GDP shares of all subspaces, ordered by g_j (see chapter 3, section 3.4 for more details).

5.3.2.2. Measures of Regional Disparity and Inequality Decomposition

Besides the above described Gini index, which represents a global measure of inequality (disparity), the study aims to identify the origin of overall inequality in the EU-25, the EU-15 and the NMS. Following Sala-i-Martin (2006) and Brakman and van Marrewijk (2008), among others, no final consensus has been worked out with respect to the development of within- and between-country income disparities in Europe due to differing spatial classification systems used in existing studies. There is some indication that especially within-country income inequality has increased, which is against the idea of general convergence as postulated by, e.g., Friedman (2005) and Sala-i-Martin (2006).[480] Moreover, increasing regional disparities are inconsistent with the European convergence objective (see Box 5.1). Preliminary empirical evidence against regional convergence in Europe has been claimed by Duro (2004), who has analyzed the period 1982-1995. Duro pointed to divergence patterns across European NUTS1/2 regions.[481]

Another complementary measure of inequality, besides the conventional global indices, is the generalized entropy index, $GE(\alpha)$, as highlighted in equation 5.3.2 (Novotný, 2007; Haughton and Khandker, 2009):[482]

$$GE(\alpha) = \frac{1}{\alpha(1-\alpha)}\frac{1}{n}\sum_{i=1}^{n}\left[1 - \left(\frac{y_i}{\bar{y}}\right)\right], \text{ for } 0 < \alpha < 1, \text{ where } \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i = \frac{Y}{N}. \qquad (5.3.2)$$

480 See OECD (2009a) for an income concentration analysis at the more aggregated TL2 level for OECD countries. For further details see Arbia *et al.* (2005), Dewhurst and McCann (2007) and Monfort (2008).

481 See also Combes and Overman (2004), Arbia *et al.* (2005), Frenken and Hoekman (2006), OECD (2009a).

482 An important aspect with regard to the different indicators is their sensitivity on differing sample sizes. To overcome the issues arising from this property, the overall number of observations in this study is constant (819 TL3 regions). However, a direct comparison between subgroups is complicated; the study only shows the time trends and the dynamics of national inequality indices.

with n = number of groups, N_i = cumulative population, N = total population, Y_i = cumulative income and Y = total income and with $\alpha = 1$ as the Theil Index T.[483] Theil's T is a particular case of the generalized entropy index. In its aggregated form, Theil's T is a measure of overall inequality/disparity (Brülhart and Traeger, 2005). When population shares equal the respective GDP shares in all regions, GDP would be distributed completely evenly, and hence, Theil's T index would be equal to zero. The index is useful in analyzing regional disparities and, most importantly, in calculating between- and within-subgroup inequality (United Nations, 2005; Novotný, 2007; Haughton and Khandker, 2009). Theil's T index, $GE(1)$, is defined as in equation 5.3.3:

$$GE(1) = T = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i}{\bar{y}} ln\left(\frac{y_i}{\bar{y}}\right) \tag{5.3.3}$$

For grouped data, a typical way to rewrite the Theil index T is presented in 5.3.4:

$$GE(1) = T = \sum_i \sum_j \left(\frac{Y_{ij}}{Y}\right) ln\left(\frac{Y_{ij}/Y}{n_{ij}/N}\right) \tag{5.3.4}$$

with Y_{ij} being the income of the ij-group; n_{ij} being absolute frequency of population in the ij-group; $Y = \sum_i \sum_j Y_{ij}$ is total income over all groups; and $N = \sum_i \sum_j n_{ij}$ is total population. Thus, the Theil index compares the relative share in the population (n_{ij}/N) with the income share of each group (Y_{ij}/Y). It is argued that the Theil index is very sensitive to the sample size. To reduce this problem, the number of observations has been held constant over time (Brülhart and Traeger, 2005; Haughton and Khandker, 2009).

It is essential to note that inequality indices show significant variation in their sensitivity to differences in different parts of the income distribution. The higher the parameter α in $GE(\alpha)$, the more sensitive is $GE(\alpha)$ to income differences at the top of the distribution; however, the more negative α is, the more sensitive is $GE(\alpha)$ to differences at the bottom of the distribution. Thus, inequality/disparity indices differ in their sensitivity to changes in the lower and upper tails of the distribution (Brülhart and Traeger, 2005). The Gini coefficient, that has been presented in the last section, is most sensitive to income differences in the middle part of the distribution. However, its sensitivity depends on the relative position of the observation in comparison to other observations. Therefore, if more regions are in the lower part of the income distribution, as is usually the case, they should obtain a stronger weight (Duro, 2004; Novotný, 2007; Haughton and Khandker, 2009).

Another frequently used measure of regional disparity is $GE(2)$, which is half the squared coefficient of variation (CV) and sensible to changes in the upper parts of the distribution. Similarly, a change of the sensitivity index in $GE(\alpha)$ to $\alpha = 0$ leads to the mean log deviation (MLD) measure, the so-called Theil's L index, $GE(0)$. With respect to different sensitivity parameters (α), it is generally argued that the dynamics of $GE(-1)$ mainly show changes of income of the poorer regional units at the bottom of the distribution, whereas $GE(2)$ is mainly responsive to changes at the upper end/tail of the distribution. $GE(1)$ is said to represent the standard case in empirical studies (Brülhart and Traeger,

483 In the following, only Theil's T is presented (see equations 5.3.3 - 5.3.6). For details on GE(-1), GE(0) and GE(2) refer to Brülhart and Traeger (2005) or Haughton and Khandker (2009).

2005; Haughton and Khandker, 2009). Accordingly, income disparity measures and their decomposition will be provided for $GE(1)$, i.e., Theil's T.

Regarding the origins of overall regional disparities in per capita income, it is fruitful to decompose global income inequality into between- and within-subgroup inequality.[484] The properties of the (non-negative) Theil index $GE(1)$ make it possible to break down overall regional disparities in such a way that the weighted sum of the index components is identical to the overall inequality index as highlighted in equation 5.3.5 (Brülhart and Traeger, 2005). Furthermore, it is argued that another advantage is that census information of the countries and regions involved are not needed (Duro, 2004; Sala-i-Martin, 2006; Brakman and van Marrewijk, 2008).

$$GE(\alpha) = GE_W(\alpha) + GE_B(\alpha), \text{ for } \alpha = 1. \tag{5.3.5}$$

Theil's T is then defined as in equation 5.3.6:

$$GE(1) = T = T_B + T_W = \left[\sum_i \left(\frac{Y_i}{Y}\right) ln \left(\frac{Y_i/Y}{n_i/N}\right)\right] + \left[\sum_i \left(\frac{Y_i}{Y}\right) T_i\right] \tag{5.3.6}$$

with $Y_i = \sum_j Y_{ij}$ as total income of the i^{th} group and $n_i = \sum_j n_{ij}$ as absolute frequency of population in the i^{th} group and $T_i = \sum_j \left(\frac{Y_{ij}}{Y_i}\right) ln \left(\frac{Y_{ij}/Y_i}{n_{ij}/n_i}\right)$ as the Theil index for the i^{th} group. $GE_B(\alpha)$ measures the share of inequality that originates from income inequality between subgroups (e.g., between countries). Within-subgroup inequality, $GE_W(\alpha)$, represents the share of inequality (or disparity) that originates from inequality within the groups under analysis (e.g., within countries) (Brülhart and Traeger, 2005; Novotný, 2007; Haughton and Khandker, 2009). Inequality decomposition is computed for several groups, i.e., the NMS, the EU-15 and the EU-25 (incl. Switzerland and Norway).

To repeat a point made earlier, the Theil index is considered to be very useful for the purpose of analyzing the origins of regional disparities. The decomposition into within- and between-subgroup disparities offers additional information in the context of divergence/convergence developments that are taking place within and between certain groups of regions. To challenge the presented research questions, global income inequality (disparity) of GDP per capita income (PPP) is decomposed into (i) inequality within nation states (within-subgroup inequality); and (ii) inequality between nation states in Europe (between-subgroup inequality). That being the case, the TL3 regions are grouped into $i \in \{1, 2, ...n\}$ subgroups. The following group classifications are analyzed in the subsequent empirical analysis: (i) the group of the EU-25+2 countries with 27 subgroups; (ii) the NMS with 10 subgroups; (iii) the EU-15 group with 15 subgroups; (iv) the group of the EU-15 and NMS with two subgroups.

484 Inequality decomposition measures should, however, require two decomposition properties (Brülhart and Traeger, 2005; Brakman and van Marrewijk, 2008): (i) subgroup consistency: the positive responsiveness of the overall inequality measure to changes in the inequality levels of constituent group as a minimum requirement; (ii) additive decomposability: overall inequality is the sum of between- and within-subgroup inequality. The mentioned properties are only satisfied by $GE(0)$ and $GE(1)$ (Duro, 2004; Arbia *et al.*, 2005; Monfort, 2008).The Gini coefficient is not decomposable in the sense of subgroup consistency. However, given the popularity and favorable properties of the Gini index, it will be used in this study as a measure for global income disparities (European and national aggregates).

5.3.3. The Development of European Income Disparities

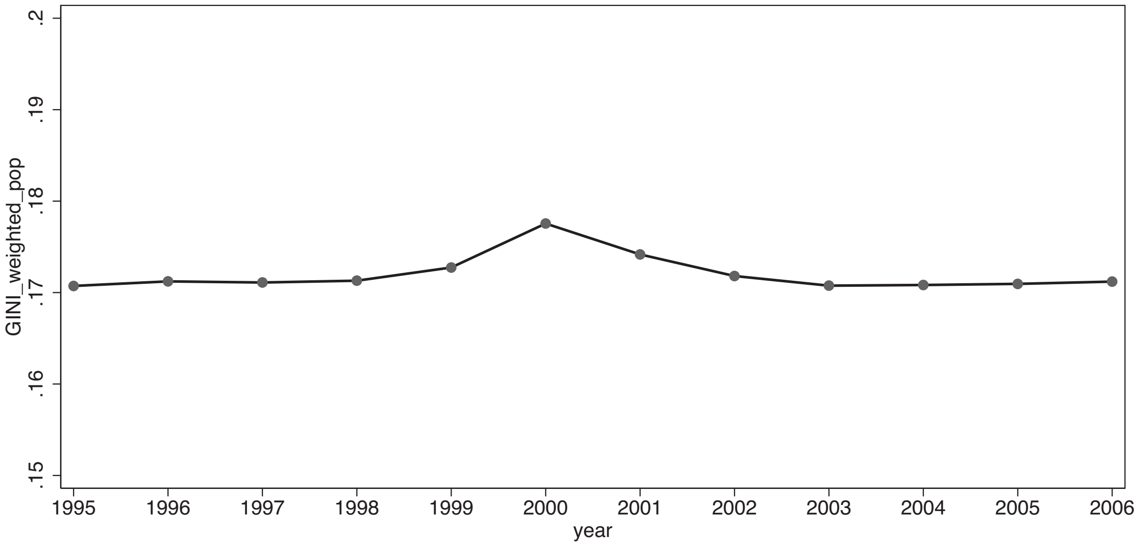
5.3.3.1. Global Income Disparities in Europe

In order to maintain a detailed and dynamic understanding of the development of European and national income disparities, the income inequality (disparity) measures for each European country since 1995 are plotted at a yearly base in figures 5.6, 5.7 and 5.8.[485] Income disparity remained rather constant within the EU-15 group, whereas the former CEE-10 (NMS) group suffered from increasing regional disparities as shown by the population weighted Gini indices (see figure 5.6). Figures 5.7 and 5.8 show the national (population weighted) Gini coefficients of GDP per capita income for the period 1995 to 2006. Countries have experienced dynamics very different from the global European trend and can be classified into three categories: (i) a decrease in inequality in Austria and Italy; (ii) a general increase in inequality in Switzerland, the Czech Republic, Denmark, Estonia, Greece, Hungary, Ireland, Lithuania, Netherlands, Portugal, Slovenia, Slovakia and the United Kingdom; (iii) an inverted U-shaped trend of income inequality in Belgium, Germany, Spain, Finland, France and Sweden. However, there is a general trend of decreasing inequality for the global sample (EU-25).

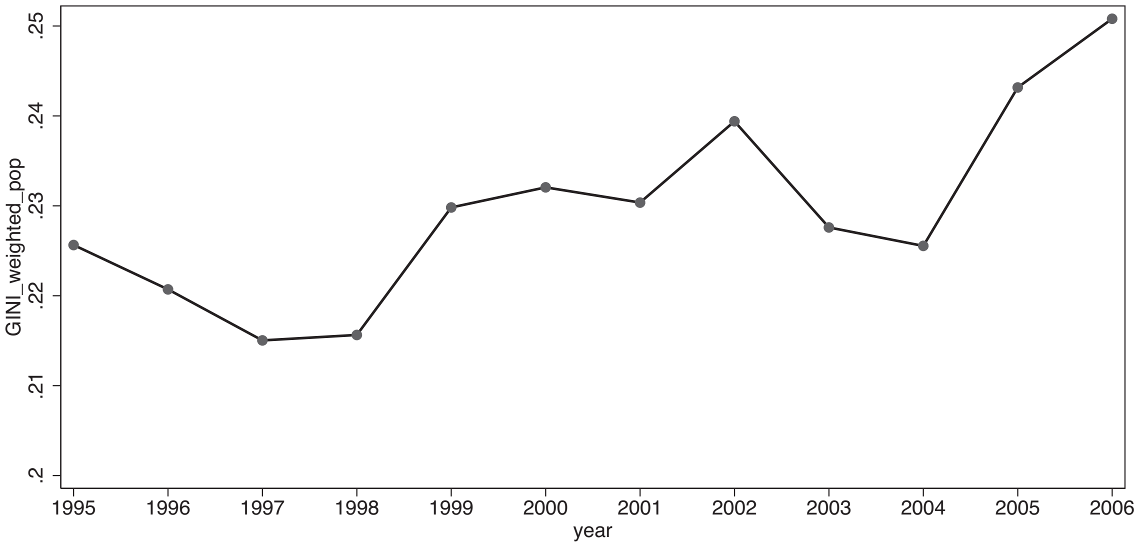
Similar to results at the TL2 level (OECD, 2009b,a), it can be argued that between-country income convergence at the TL3 level is accompanied by within-country income divergence, meaning that there is a significant increase in income inequality within several European countries.[486] However, within-country divergence is stronger at the TL3 level; TL2 disparities are weaker due to aggregation/averaging (Arbia and Petrarca, 2010). Besides the varying dynamics of Gini coefficients of GDP per capita, figures 5.6, 5.7 and 5.8 also show a trend of increasing within-country income disparities for several countries, which is in line with conclusions from new economic geography frameworks (see theoretical considerations in chapter 2) (see also Puga, 2002; Rodríguez-Pose and Fratesi, 2007). It is visible that several European countries have experienced a significant increase in income inequality, meaning that convergence within countries does not dominate the European picture. Cross-country convergence (between countries) is in most cases accompanied by significant regional divergence within countries (Williamson, 1965). According to a recent study of the OECD, the European TL2 regions can be divided into two groups in terms of average yearly growth rates: (i) a "convergence" group which shows the following growth rate characteristics: minimum 1.5%, maximum 6.6%, median 2.5%, average 2.7%; (ii) a "divergence" group which shows the following values: minimum 1.7%, maximum 5.4%, median 2.9%, average 3.1%. These results support the findings in this study, i.e., evident divergence in several backward countries (OECD, 2009b,a).

[485] For similar results regarding inequality decomposition refer to Paas and Schlitte (2007). Nevertheless, the authors applied a different spatial classification system and offered only results regarding GE(1).

[486] In opposition to this study, the OECD (2009a,b,c) predominantly centers the TL2 level (i.e., NUTS1/2 level), which is much more aggregated compared to the TL3 level used in this study. The OECD concluded that *"countries that have experienced diverging regional income disparities tended to show faster real GDP growth rates at the national level"* (OECD, 2009b, 21; see also OECD, 2009c, 32-35).



(a) Weighted Gini coefficient GDP/capita (PPP) EU-15 (1995-2006)



(b) Weighted Gini coefficient GDP/capita (PPP) NMS (1995-2006)

Fig. 5.6. Development of regional disparities in GDP/capita (PPP) by group
Source: own calculations and illustration.

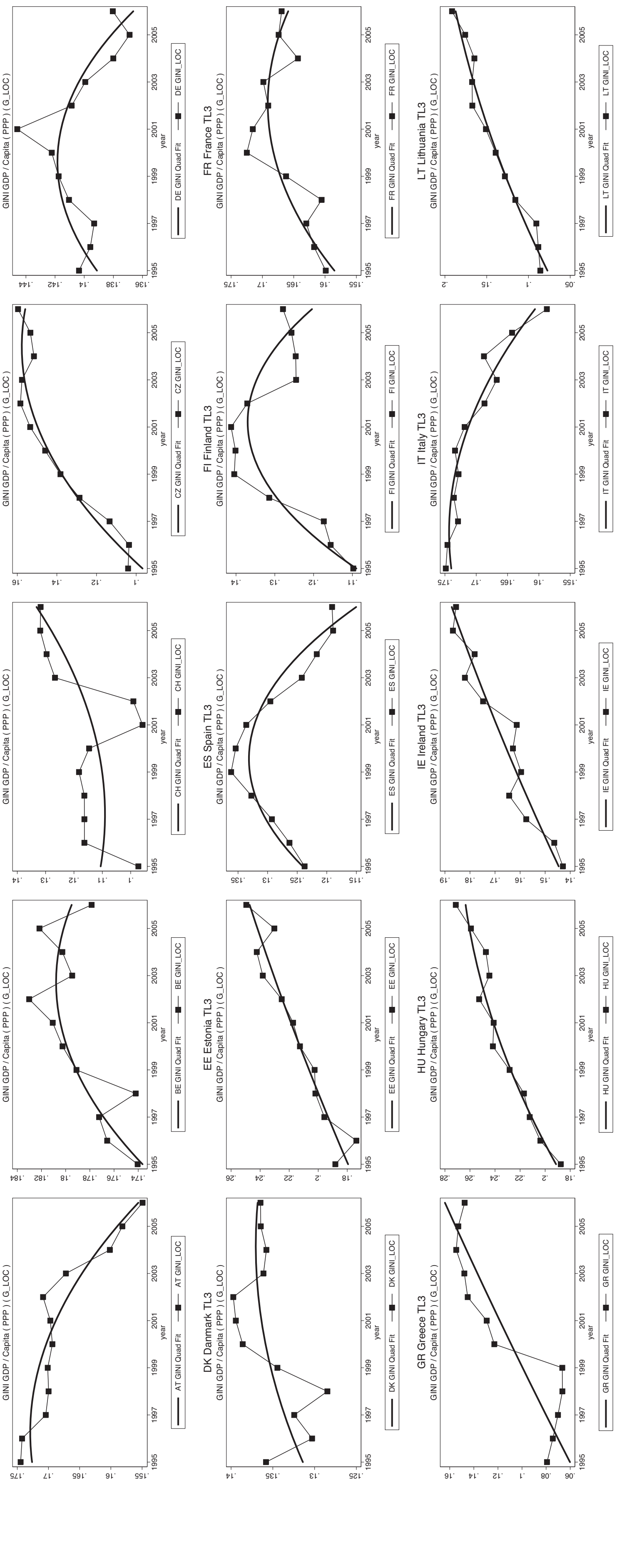


Fig. 5.7. Locational Gini coefficients of GDP per capita (PPP) (a)
Source: own calculations and illustration.

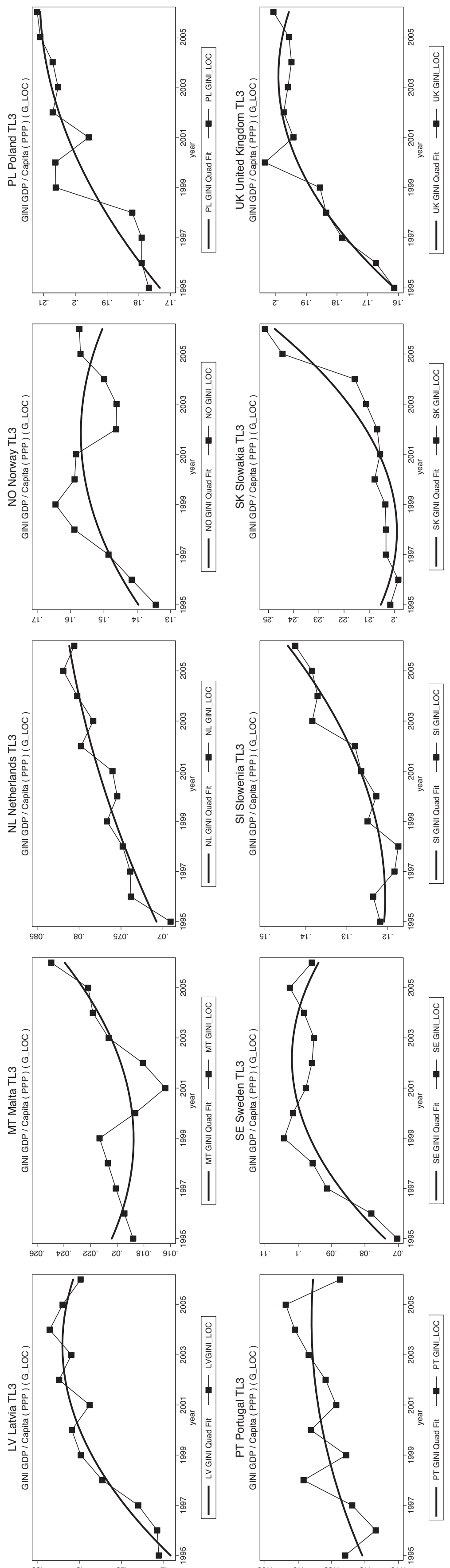


Fig. 5.8. Locational Gini coefficients of GDP per capita (PPP) (b)
Source: own calculations and illustration.

5.3.3.2. Regional Disparities within and between European Countries

As has been argued in the previous sections, another pivotal consideration concerns the development of regional disparities within and between European member countries. The following figures illustrate the development of income inequality by subgroups as proposed in the previous section 5.3.2.2; special emphasis is placed on Theil's T, i.e., GE(1).

The graphs in figure 5.9 focus on the development of GDP per capita inequality of the entire population of European regions (i.e., the 817 TL3 regions, except Cyprus and Luxembourg, that represent the EU-23, Switzerland and Norway) between the years 1995 and 2006. It is obvious from the graphs that between- and within-subgroup disparities matter for the development of overall (global) disparity. Besides the fact that overall regional disparities (graphs on the left) have decreased in the entire population, i.e., GE(-1) to GE(2), the share of between-subgroup disparities (graphs on the right) has decreased by approximately 15% since the year 1995 (GE1between819TL3), meaning that on average convergence between countries took place. At the same time, within-subgroup disparities (GE1within819TL3) have relatively increased, which means that Europe consists of a meaningful number of countries that suffer from considerable increases in regional income inequality within national borders (i.e., within-country regional divergence).

However, in order to analyze the development of regional disparities more closely with respect to the European integration process, the entire population of the 819 European regions is divided into two groups; the group of EU-15 regions with countries as subgroups (see figure 5.10) and the group of NMS regions with countries as subgroups (see figure 5.11).[487] One should expect different developments and dynamics, similar to differences regarding EPO patenting activity and research networks (see chapter 3 and 4).

Figure 5.10 shows that the EU-14 group (650 regions, without Luxembourg) features a very similar overall development of regional income disparities compared to the entire population of the 817 European regions. A decrease in overall income inequality (disparity) since 1995 is visible. Between-subgroup inequality (GE1betweenEU-15) and within-subgroup inequality (GE1withinEU-15) have decreased. However, between subgroup inequality is at a much lower level compared to within-subgroup inequality, indicating that overall income inequality stems mainly from inequality within countries.[488]

A very different picture emerges from the decomposition of income inequality in the case of the NMS regions. Figure 5.11 highlight the results based on the inequality decomposition. The subgroups are again defined with respect to national borders (122 NMS regions in 9 countries).[489] The graphs in figure 5.11 clearly show a significant increase of within-subgroup inequality (GE1withinNMS), which has been accompanied by a strong decrease in between-subgroup inequality (GE1betweenNMS). However, the decrease in between-subgroup inequality, which represents cross-country convergence, could not compensate for the strong increase in within-subgroup inequality, that has led to an overall increase in

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[487] For a similar interpretation at the more aggregated level of NUTS2 regions see Monfort (2008).

[488] For a comprehensive review of existing inequality studies at the national level see Novotný (2007) and de Dominicis *et al.* (2008). Refer also to Combes and Overman (2004).

[489] Cyprus is a single regions and thus within-country inequality cannot be decomposed into a within- and between-country component.

income disparities in the NMS group. Thus, the graphs in figure 5.11 clearly exhibit an increase in income disparities, which stems predominantly from divergence at the regional level within countries.[490]

Finally, in an alternative analysis, the subgroup borders are redefined in terms of administrative borders of the EU-15 and NMS groups. Between-subgroup inequality originates from differences between the EU-15 and NMS group. Within-subgroup inequality originates from regional disparities within the two groups. Figure A.46 (appendix) summarizes the results of this inequality decomposition, which are quite similar to the ones already presented above. Again, it is visible that regional disparities among regions within the groups have increased since the 1990s, whereas regional disparities between the two groups have decreased.

To conclude, the inequality decomposition demonstrates that regional income disparities have in general decreased within Europe, which is mainly a result of decreasing disparities between European member states, reflecting the closing of income gaps among European countries. On the contrary, income disparities among regions within the borders of European countries have increased since the mid 1990s, indicating the emergence of national core-periphery structures relating to GDP. It is evident from the above presented results that the global decline in income disparities among European countries, and in Europe as a whole, coincides with increasing regional disparities within member states. Consequently, the developments since the 1990s have not prevented disparities to increase in some countries; particularly in those countries that recently joined the European Union.

Another shortcoming of empirical studies on the European case is the lack of growth regressions at the TL3 level (Paas and Schlitte, 2007). Therefore, a final consideration of this chapter concerns European regional growth regressions. Section 5.4 presents regional growth regressions for the same spatial classification system as has been described and discussed above and analyzed in chapters 3 and 4 (i.e., TL3 regions in the EU-15 and NMS). Besides a short review of the canonical absolute and conditional convergence concept, the following part primarily contributes with regression models that extend the standard conditional convergence model with several covariates that control for (i) the regional neighborhood structure and potential spatial interdependence, (ii) regional typologies (i.e., urban, rural, intermediate, metro and capital regions), and (iii) regional technology structures and research activities (i.e., regional EPO patenting activity).

5.4. Research Activity, Settlement Structure and Regional Growth

5.4.1. Income Levels and Regional Growth: A Descriptive Overview

A still controversial research question is whether or not European regions are converging or diverging since the 1990s and which factors are the drivers of divergent regional growth.

[490] Note that the results are supported by a recent study of the OECD, although their study centers the more aggregated TL2 level (OECD, 2009a,b).

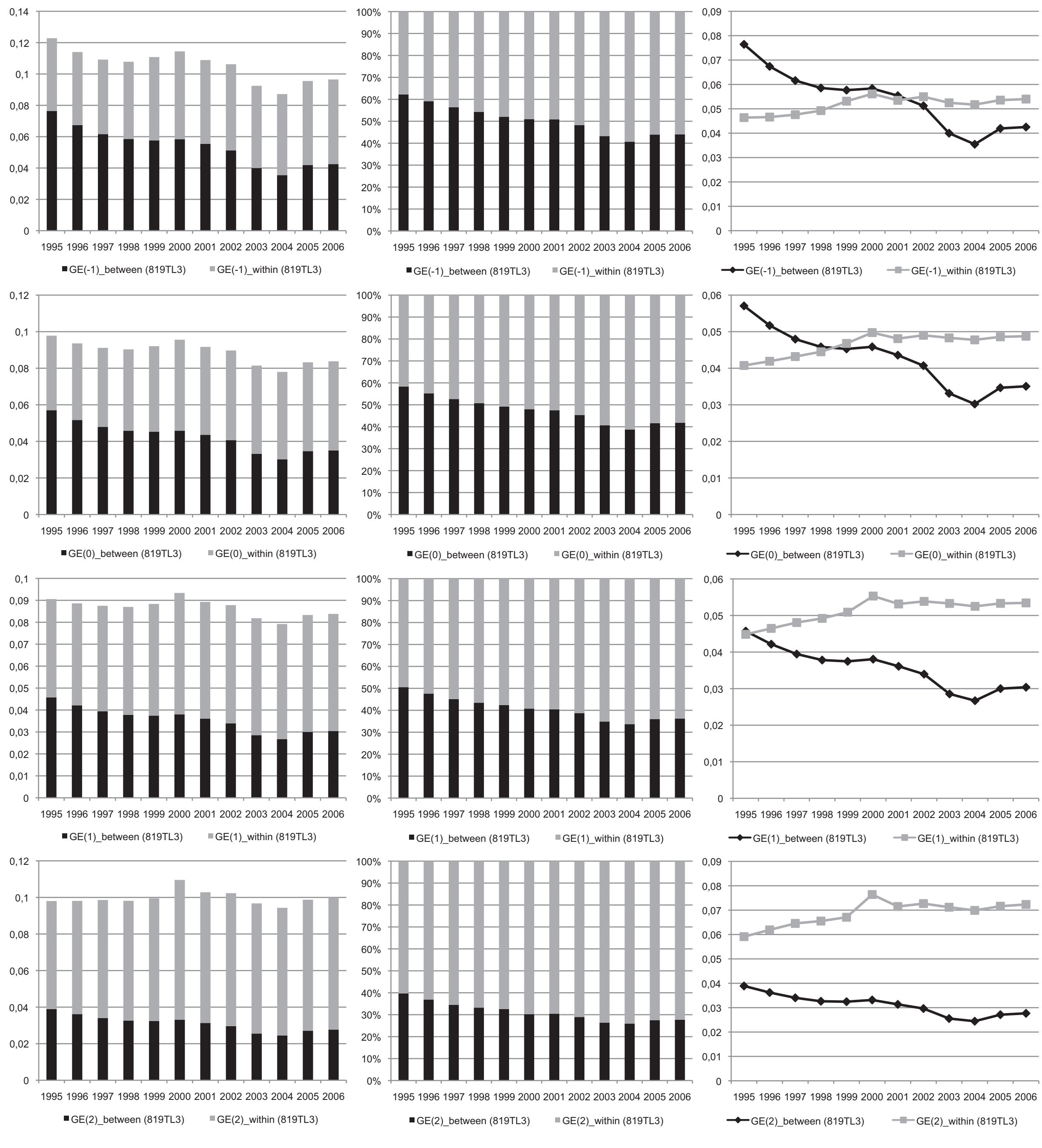

Fig. 5.9. Income inequality decomposition: EU-23, CH, NO
Source: own calculations and illustration. *Notes:* GDP per capita in the EU; inequality composition is done for GE(-1), GE(0), GE(1), GE(2). Sample includes 773 EU-23 regions and Switzerland and Norway. Cyprus and Luxembourg excluded due to impossible within-country inequality decomposition. Subgroups represented by country ID.

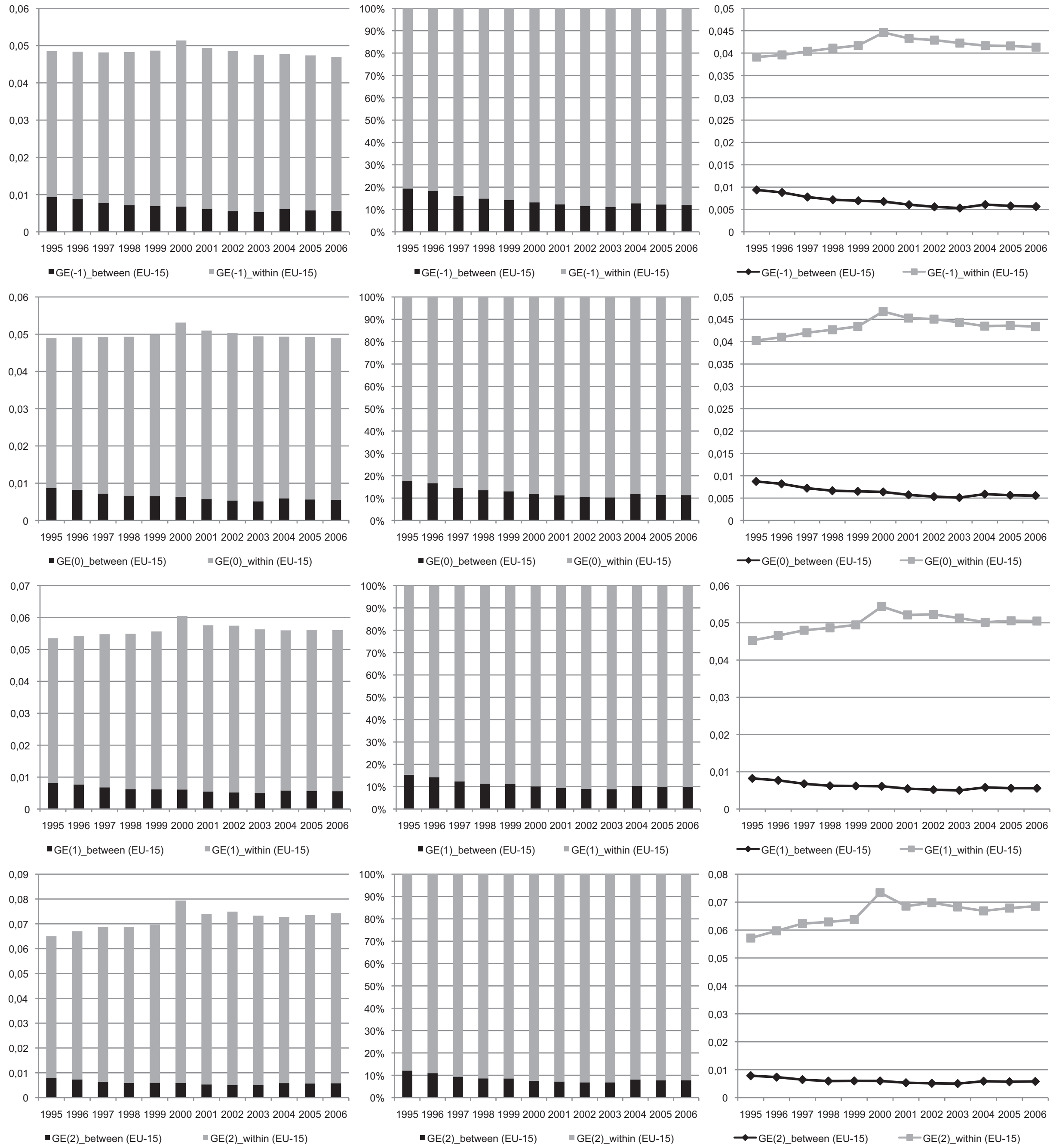

Fig. 5.10. Income inequality decomposition: EU-14 group
Source: own calculations and illustration. *Notes:* GDP per capita in the EU; inequality composition is done for GE(-1), GE(0), GE(1), GE(2). Sample includes 650 EU-14 regions. Luxembourg excluded due to impossible within-country inequality decomposition. Subgroups represented by country ID.

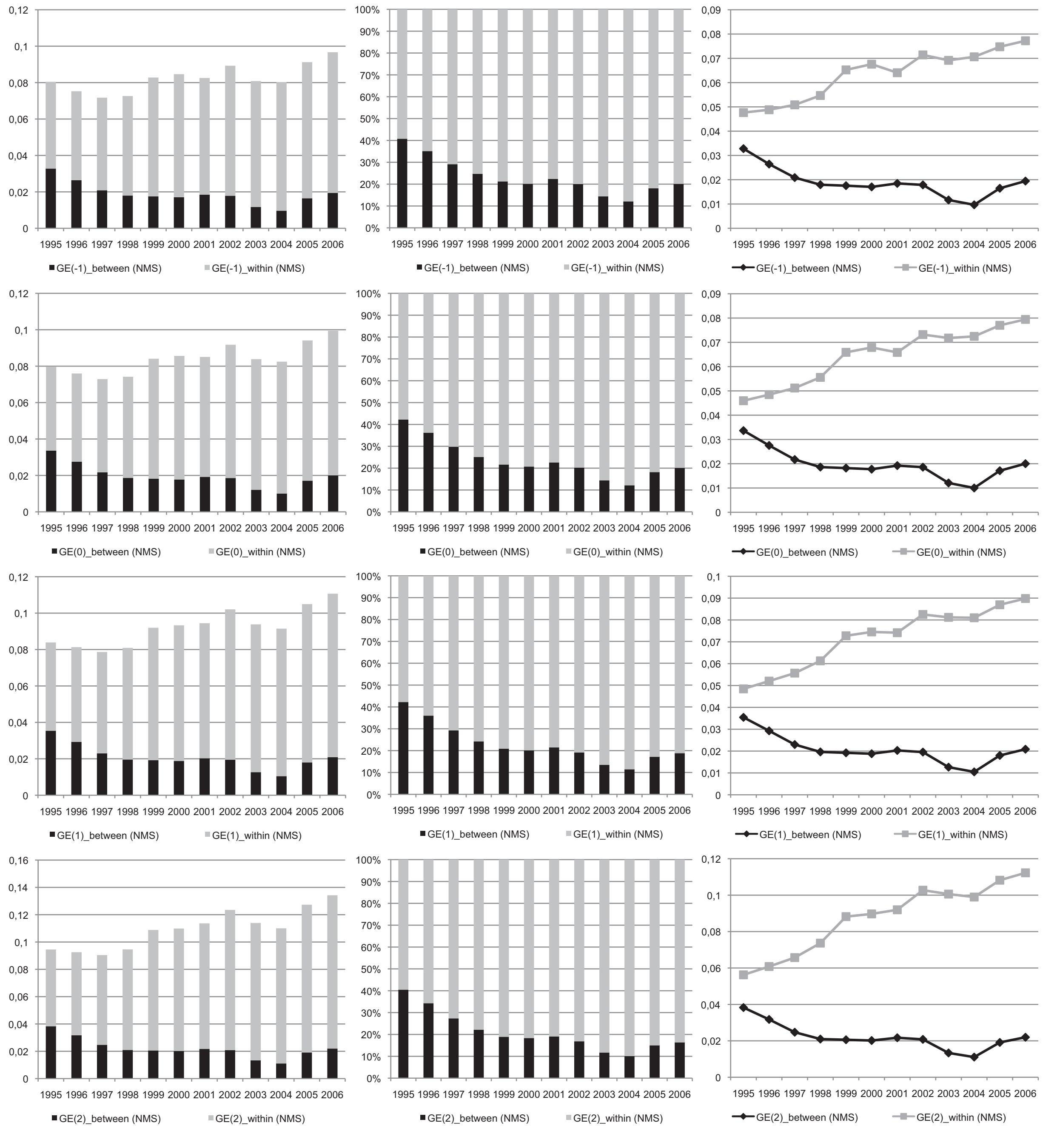

Fig. 5.11. Income inequality decomposition: NMS group
Source: own calculations and illustration. *Notes:* GDP per capita in the NMS; inequality composition is done for GE(-1), GE(0), GE(1), GE(2). Sample includes 122 NMS regions. Cyprus excluded due to impossible within-country inequality decomposition. Subgroups represented by country ID.

The subsequent scatter plot (figure 5.12) illustrates initial GDP per capita levels in 1995 (abscissa) for 651 regions (the EU-15 group) and their growth rate (ordinate). The figure seems to illustrate a kind of regional convergence, although we cannot draw statistically robust conclusions from simple scatter plots. Identically, figure 5.13 highlights this relationship for NMS regions. Finally, both subgroups are combined (figure 5.14). It is visible from the combined scatter plot, that the enlarged group of EU-25 regions (entire population) suffers from structural differences. Mainly all NMS regions are located in the upper-left corner of the figure; the EU-15 regions are determined by rather smaller growth rates, although they have reached very similar levels of GDP per capita. Related to this observation, several studies have analyzed the two groups of regions separately (Paas and Schlitte, 2007, 2008).

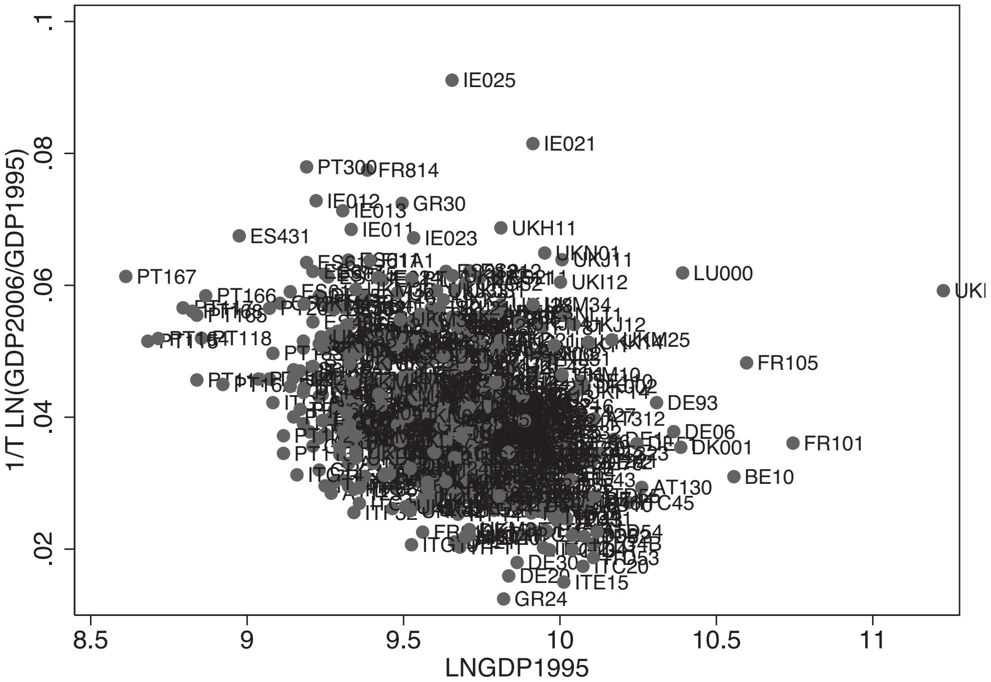

Fig. 5.12. Scatterplot GDP/capita level (1995) vs. growth rate (1995-2006), EU-15
Source: own calculations and illustration. *Notes:* 651 observations included; GDP in PPP.

5.4.2. Unconditional Convergence and European Regional Growth

The relationship between the initial level of GDP per capita and growth in per capita GDP is generally estimated by application of a standard econometric growth model (log-linear specification). It includes the income growth parameter $ln(\frac{y_{i,t+T}}{y_{i,t}})$ as dependent variable and the initial level of income $ln(y_{i,t})$ as explanatory variable (see equation 5.4.1). This corresponds to the concept of unconditional (absolute) β-convergence and can be applied in a spatial context to regions ($i = 1, ..., N$), derived from the neoclassical growth model (Barro and Sala-i-Martin, 2003; Hagemann, 2004; Solow, 2007). It applies to the case of similar structural characteristics between observations (Mankiw *et al.*, 1992; Barro and Sala-i-Martin, 1992). Results of studies conducted at the regional level have been reported

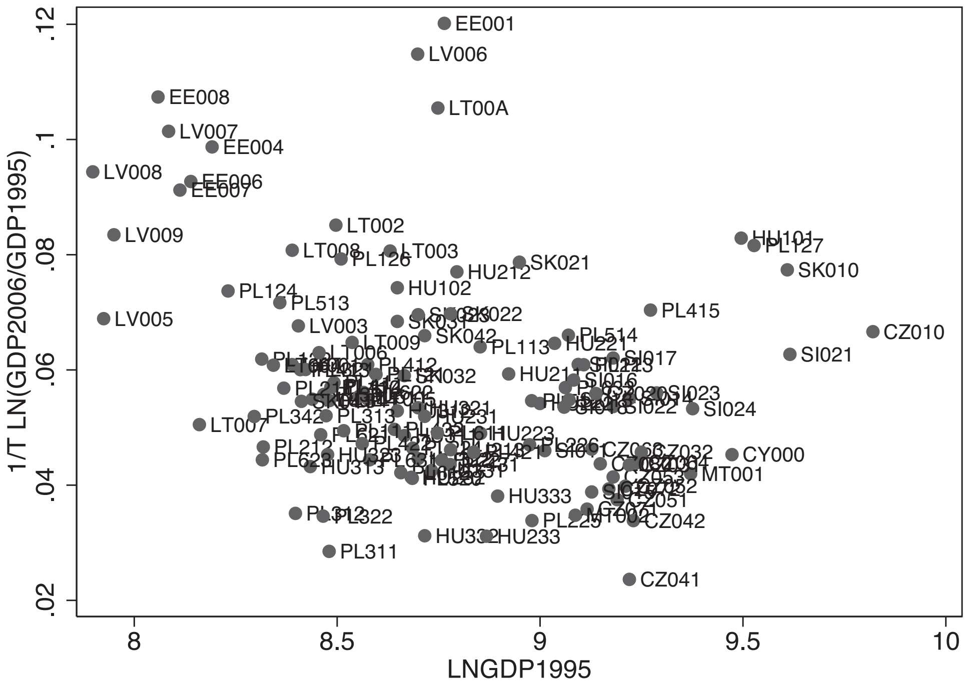

Fig. 5.13. Scatterplot GDP/capita level (1995) vs. growth rate (1995-2006), NMS
Source: own calculations and illustration. *Notes:* 123 observations included; GDP in PPP.

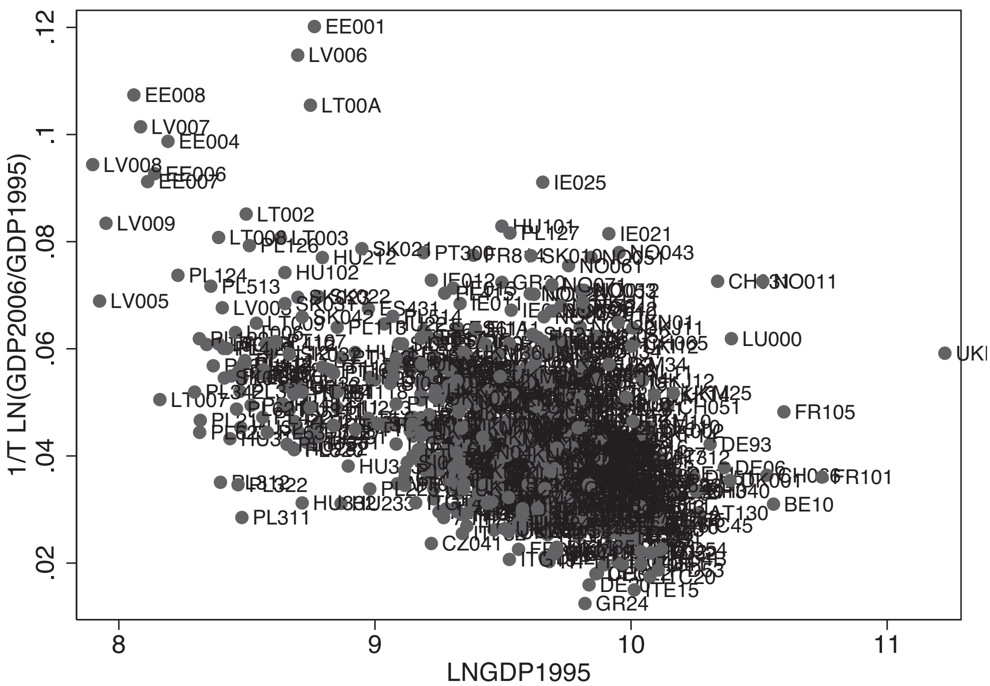

Fig. 5.14. Scatterplot GDP/capita level (1995) vs. growth rate (1995-2006), EU-25
Source: own calculations and illustration. *Notes:* 813 observations included; GDP in PPP.

by Bräuninger and Niebuhr (2005), Abreu *et al.* (2005), Bräuninger and Niebuhr (2008), OECD (2009a) and Crespo Cuaresma *et al.* (2009b), among others.

$$\frac{1}{T} ln\left(\frac{y_{t+T}}{y_t}\right) = \beta_0 + \beta_1 ln(y_t) + \varepsilon \qquad (5.4.1)$$
$$\varepsilon \sim N(0, \sigma_\varepsilon^2 I)$$

T is the length of the analyzed period (here 11 years); ε_i is a $(n \times 1)$ vector of independently and identically distributed disturbances.[491] Tests of absolute β-convergence are generally plausible when the object of study is within-country convergence, because knowledge and technology bases, institutions, geography and standard of living are assumed to be quite similar within countries.[492]

Table 5.1 summarizes absolute convergence regression results for the EU-25, the EU-15 and the NMS group (TL3 regions). In addition, national convergence estimates are reported in the subsequent tables, if the initial GDP level coefficient is significant (see tables 5.2 and 5.3).[493] A first result is that growth regressions without national controls (models 1-3) show significant convergence tendencies (initial GDP level is significant and negative) (see also Frenken and Hoekman, 2006). However, when national controls are included, the convergence speed in the EU-15 and EU-25 group slows down (models 4, 5). Moreover, the coefficient of initial GDP completely changes its sign for the NMS group when national dummy variables are incorporated, meaning that regions in the NMS group are diverging (model 6). This result is in line with the aforementioned results regarding Gini indices and inequality decomposition.

Furthermore, regional growth regressions (absolute convergence) are reported for selected countries in tables 5.2 and 5.3. It is obvious that especially NMS countries, e.g., the Czech Republic, Estonia, Hungary, Latvia, the Slovak Republic, Slovenia, show significant and positive coefficients of the initial GDP per capita level, meaning that these countries are determined by regional divergence.[494] Absolute convergence seems to be absent as regional units differ in several ways (e.g., patenting activity, regional size, population density, GDP level). The varying levels of technological knowledge and research activities of European regions, i.e., patenting and co-patenting activities, have been already presented and discussed in the previous chapters. Therefore, the standard empirical approach has to be

491 Convergence speed is not of central interest in this study. According to the standard growth regression methodology, the rate of convergence is obtained by estimating β_1 for the initial income level and re-parameterizing it via $b = -ln(1 + \beta T)/T$ in order to compute convergence speed and half-life (Bräuninger and Niebuhr, 2005).

492 Given the cross- sectional data in this study, there might exist three types of departures from this assumption: (i) heteroscedasticity, (ii) spatial autocorrelation, (iii) outliers and parameter heterogeneity. While the first deviation leads inefficiency of OLS, the last two might seriously bias the estimates (see also Bräuninger and Niebuhr, 2005; Geppert and Stephan, 2008; OECD, 2009a).

493 Insignificant estimations are not reported. The regressions are generally based upon heteroscedasticity-consistent standard errors (Huber–White standard errors) to control for potential heteroscedasticity of unknown form (Stata, 2009, 2010).

494 See Frenken and Hoekman (2006) for very similar results.

Table 5.1. Unconditional and conditional convergence for EU-25, EU-15 and NMS

Model	(1) EU-15	(2) EU-25	(3) NMS	(4) EU-15	(5) EU-25	(6) NMS
dependent variable: $1/Tln(y_{i,2006}/y_{i,1995})$						
CTRYDUMMY	no	no	no	yes	yes	yes
GDPLEVEL	-0,0118***	-0,0164***	-0,0132**	-0,0054***	-0,0116***	0,0203***
	(0,0118)	(0,0014)	(0,0046)	(0,0017)	(0,0016)	(0,0044)
t-value	-6,31	-11,68	-2,86	-3,16	-7,21	4,62
R-squared	0,0958	0,2691	0,08	0,50	0,48	0,59
N	645	768	123	645	768	123

Source: own estimations. *Notes:* growth regressions for the period 1995-2006 with and without national controls (CTRYDUMMY); country dummy variables (4-6) and constant (1-6) not reported; robust standard errors in parentheses. Huber and White robust-sandwich estimator reported in table. HC3, robust and clustered regressions were additionally executed; signs and significance did not change. Details available upon request.

extended in order to deal with regional heterogeneity; i.e., national controls and several covariates.[495]

Table 5.2. Robust OLS estimation results: national growth regressions (1)

Model	(7) CZ	(8) DE	(9) EE	(10) ES	(11) HU	(12) IT
dependent variable: $1/Tln(y_{i,2006}/y_{i,1995})$						
GDPLEVEL	0,0355***	-0,0126***	0,0328***	-0,0079*	0,0304***	-0,0137***
	(0,0072)	(0,0034)	(0,0101)	(0,0044)	(0,0096)	(0,0017)
t-value	4,95	-3,73	3,25	-1,80	3,18	-8,26
R-squared	0,3798	0,1597	0,6314	0,0768	0,2358	0,3707
N	14	97	5	50	20	103

Source: own estimations. *Notes:* National cross-sectional growth regressions for the period 1995-2006; robust standard errors in parentheses; constant not reported; Huber and White robust-sandwich estimator reported in table. HC3, robust and clustered regressions were additionally executed; signs and significance did not change. Details available upon request.

5.4.3. Conditional Convergence and Regional Growth in Europe

5.4.3.1. Conditional Convergence and Regional Growth

Testing for conditional convergence means to incorporate regions' internal factors, which assumes different steady states with a $k \times 1$ vector of regions' internal factors ($X_{i,t}$) as in the testable model 5.4.2 (Mankiw *et al.*, 1992; Hagemann, 2004; Arbia *et al.*, 2005). $X_{i,t}$ is a standard vector of exogenous explanatory variables (exogenous covariates), which primarily determines the growth rate with the parameter β_2 (besides the effect from the

495 In case of conditional convergence estimations the choice of the explanatory variables is crucial as they differentiate regions' steady states.

Table 5.3. Robust OLS estimation results: national growth regressions (2)

Model	(13) LT	(14) PT	(15) SK	(16) SL	(17) UK
dependent variable: $1/Tln(y_{i,2006}/y_{i,1995})$					
GDPLEVEL	0,0703***	-0,0119*	0,0175***	0,0157**	0,0070**
	(0,2345)	(0,0063)	(0,0062)	(0,0070)	(0,0028)
t-value	3,00	-1,91	2,84	2,24	2,50
R-squared	0,4721	0,1075	0,5744	0,1532	0,0285
N	10	30	8	12	133

Source: own estimations. *Notes:* National cross-sectional growth regressions for the period 1995-2006; robust standard errors in parentheses; constant not reported; Huber and White robust-sandwich estimator reported in table. HC3, robust and clustered regressions were additionally executed; signs and significance did not change. Details available upon request.

initial GDP level via β_1).[496]

$$\frac{1}{T}ln\left(\frac{y_{t+T}}{y_t}\right) = \beta_0 + \beta_1 ln(y_t) + \beta_2 ln(X_t) + \varepsilon \qquad (5.4.2)$$
$$\varepsilon \sim N(0, \sigma_\varepsilon^2 I)$$

Regarding regional studies, growth regressions normally incorporate regional and national dummy variables (see table 5.4).[497] Besides national dummy variables (CTRYDUMMY), which are in general applied in international convergence estimations, growth regressions additionally include several covariates and controls as presented in table 5.4. The study implements dummy variables for national border regions (NATBORDER) and European border regions (EUBORDER), testing the hypothesis that border regions suffer from lower growth rates due to their peripheral geographic location. Additionally, several agglomeration controls are included, e.g., population density (POPDENSITY), level of urbanization and closeness to a large city/a large local market (URBAN, METRO), rural/peripheral areas (RURAL). Accordingly, regions are classified into metro regions (METRO), urban regions (URBAN), intermediate regions (INTERMEDIAT) and rural areas (RURAL).[498] Metro regions are those units, which are highly populated and incorporate a large city center with sufficient population size and density (European Union, 2009). Urban, intermediate and rural areas are defined according to an alternative classification with respect to population density, absolute population and market size, and closeness to a city center

496 Note that β is the marginal effect from x on y with $\partial y/\partial x = \beta$.

497 The general model description in this study is related to the regression setup proposed by OECD (2009a). In comparison to the TL2 level regressions in OECD (2009a), this study offers TL3 level regressions. Furthermore, several ideas for covariates and methodological aspects are related to the regressions in Arbia *et al.* (2005), Bräuninger and Niebuhr (2005), Paas and Schlitte (2007), Bräuninger and Niebuhr (2008), Geppert and Stephan (2008) and Paas and Schlitte (2008).

498 Figure A.47 in the appendix highlights the OECD (2010) definition of urban, intermediate and rural areas for the analyzed sample. It shows that most European regions correspond to the intermediate and rural classification. All spatial dummy variables in the regressions represent the regional typology in the year 1995.

with specific numbers of inhabitants (OECD, 2010).[499] Moreover, a capital region control variable (CAPITAL) is used, which controls for the attribute that the TL3 region hosts the administrative center of the national economy.[500] The hypothesis is, that the capital region dummy should be at least significant and positive in the regressions for the NMS group if capital regions exhibit higher growth rates. A small number of studies confirmed strong core-periphery structures in the NMS at the regional level, originating from high growth rates in capital regions and poor peripheral regions (see, e.g., Paas and Schlitte, 2008).[501]

Besides the regional typology, which controls for the average state of settlement between 1995 and 1997, the study additionally controls for employment (and thus implicitly for production) structures by application of a very simple sectoral classification (due to data constraints). The employment shares in industry (INDUSTRY) and services (SERVICES) are implemented for all European TL3 regions for the initial year (OECD, 2003, 2009d).[502]

Finally, the analysis controls for the region-specific technology and knowledge bases and research activity in terms of population corrected EPO patent applications in non-high-technology (NHTEPOPAT) and high-technology fields (HTEPOPAT) at the regional level (OECD, 2009a,f,e). The rationale is that technologically leading regions show in general higher levels of EPO patent applications, which serve as a proxy for codified (analytic) knowledge bases. Moreover, these covariates implicitly control for human capital in high-technology and non-high-technology fields (see OECD, 2009a,b). Besides the distinction into non-high-technology and high-technology EPO patents, the analysis also incorporates the overall number of EPO patent applications (per capita). The hypothesis is that there is a significant relationship between European regions' average annual growth rates in GDP per capita (PPP) and regions' technology structure, which is proxied by regions' EPO patent applications (codified knowledge). The hypothesis is that EU-15 and NMS regions' EPO high-technology patent application densities are significant and positive in growth regressions. Non-high-technology EPO patent applications are assumed to show a significant and positive coefficient in NMS regressions, as these regions are on average technologically backward compared to EU-15 regions (see also chapter 3, sections 3.4 and 3.5).[503] As has been already shown in chapters 3 and 4, leading innovative European regions are located in the western part of Europe. These places are responsible for the major fraction of European patent applications and are hosting the majority of EPO inventors. EPO patent applications represent an established approximation for research activity and are assumed to be associated with regional human capital structures (Griliches, 1990; OECD, 2009a).

499 Statistically, metro regions are agglomerations of at least 250.000 inhabitants and represent a combination of NUTS3 regions. An agglomeration is represented by at least one NUTS3 region; however, in most cases the metro regions consist of several units. If in an adjacent NUTS3 region more than 50% of the population also lives within this agglomeration, it is included into the metro unit.

500 Due to the level of aggregation, several neighboring regions may share this attribute.

501 According to this study, the capital region dummy in the NMS regressions is significant and positive.

502 Unfortunately, there exist no 2-digit or 3-digit industry employment data at the TL3 regional level for the whole population of 819 regions; neither for all EU-15 countries.

503 For visualization purpose, figure A.48 in the appendix show the spatial distribution of EPO patent applications per million inhabitants (patent densities) for the initial year (average value 1994-1996). For further details refer to chapter 3 and 4.

Regarding the methodological design of regional growth analyses, panel studies generally center changes within countries over time, while cross-sectional studies examine differences between countries and regions. Moreover, it is also argued that cross-sectional studies investigate long-run relationships, whereas panel studies look at relationships at a short/medium viewpoint (see, e.g., Arbia *et al.*, 2005; Geppert and Stephan, 2008). Since the explanatory variables of the growth regression models in this study rather represent time-invariant characteristics of European regions, e.g., regional typology, time-invariant employment shares, national controls (dummy variables), and extremely time-invariant patent densities, the focus is restricted on cross-sectional regressions. Accordingly, the following regressions are rather interested in broad categories of factors rather than in the influence of specific growth determinants. Although information on regional capital stocks does not exist, the regional typology is considered to implement additional information (and variation), i.e., infrastructure, capital stock, human capital, local market size (Bräuninger and Niebuhr, 2005; Geppert and Stephan, 2008).[504] Similarly, Geppert and Stephan (2008, 198) argued that,

> "[as] most of the explanatory variables, country and settlement-type dummies, represent time-invariant characteristics of regions, it is not possible to apply the standard approaches of panel data analysis. The influence of these broad categories of factors on regional income has to be evaluated in a cross-sectional setting."

Accordingly, the following empirical analysis depicts the significance of regional dummy variables, especially of the regional typology (i.e., settlement structure), in a cross-sectional econometric setting. The distribution of EPO patenting activity is highly skewed but persistent and thus represents another time-invariant feature of the TL3 regions under analysis. Covariates and dummy variables are presented and defined in table 5.4; the expected signs of the estimates are presented in table 5.5.

It can be concluded from the previously presented national growth regressions in tables 5.2 and 5.3 that the EU-15 and NMS group show very different growth patterns (see also Paas and Schlitte, 2007). Therefore, this study follows several contributions and splits the EU-25 group into an EU-15 and NMS regression group for which regressions are run separately. The results of the a-spatial conditional convergence regressions are reported in tables 5.6 (EU-15) and 5.7 (NMS). Due to potential heteroscedasticity, the conditional growth models are estimated with White-robust heteroscedasticity-consistent standard errors for inference purpose.[505]

Another issue in regional regressions is potential spatial interdependence of observations (see also chapter 4, section 4.1). Spatial econometrics can handle this issue with the help of (i) spatial lags of the dependent variable, or (ii) by allowing interdependence within the

[504] For similar interpretations refer to Geppert *et al.* (2005) and OECD (2009a). Moreover, several covariates could not be incorporated into a panel analysis due to severe data constraints at the TL3 level.

[505] Although coefficients should not be biased, inference of classical least square estimations would lead to biased standard errors and thus unreliable inference. HC3 least-square estimator and the intragroup-cluster correlation estimator have also been applied; the latter estimator allows for intra-group interdependence between observations, which represents an alternative to spatial models (group ID equals country ID), i.e., all regions within a country form a cluster.

Table 5.4. Dependent variable, covariates and controls

dependent variable:		
GDPGROWTH	$1/T \ln(y_{i,2006}/y_{i,1995})$	average annual GDP per capita growth rate (PPP)
explanatory variables:		
GDPLEVEL	$\ln(y_{i,t})$	GDP per capita level (PPP)
$\rho GDPLEVEL$	$W[1/T \ln(y_{i,t+T}/y_{i,t})]$	spatial lag of average annual GDP per capita growth rate (PPP)
INDUSTRY	$\ln(E_{1i}/\sum_1^3 E_i)$	share of total regional employment in industry sector
SERVICES	$\ln(E_{2i}/\sum_1^3 E_i)$	share of total regional employment in service sector
EPOPAT	$\ln(PAT_i/pop_i)$	total EPO patent applications per million population; proxy for research activity and technological development
HTEPOPAT	$\ln(HPAT_i/pop_i)$	high-tech EPO patent applications per million population; proxy for research activity in high-technology
NHTEPOPAT	$\ln(NHPAT_i/pop_i)$	non high-tech EPO patent applications per million population; proxy for research activity in non high-technology
POPDENSITY	$\ln(pop_i/space_i)$	population per square kilometer
CAPITAL	χ_{1i}	regional dummy [0;1]; predominantly capital areas
METRO	χ_{2i}	regional dummy [0;1]; predominantly metropolitan areas
URBAN	χ_{3i}	regional dummy [0;1]; predominantly urban areas (see figure A.48, appendix)
INTERMEDIAT	χ_{4i}	regional dummy [0;1]; predominantly intermediate areas (see figure A.48, appendix)
RURAL	χ_{5i}	regional dummy [0;1]; predominantly rural areas (see figure A.48, appendix)
EUBORDER	κ_{1i}	regional dummy [0;1]; regions sharing an extra-EU border
NATBORDER	κ_{2i}	regional dummy [0;1]; regions sharing a national border
CTRYDUMMY	ψ_i	national control variable [0;1], AT, BE, CY, CZ, DE, DK, EE, ES, FI, FR, GR, HU, IE, IT, LT, LU, LV, MT, NL, PL, PT, SE, SI, SK, UK (see also table B.3, appendix)

Table 5.5. Expected signs of explanatory variables

$\beta(URBAN) > 0$	$\beta(INTERMEDIAT) > 0$	$\beta(\rho) > 0$
$\beta(CAPITAL) > 0$	$\beta(METRO) > 0$	$\beta(POPDENSITY) > 0$
$\beta(INDUSTRY) > 0$	$\beta(SERVICES) > 0$	$\beta(GDPLEVEL) < 0$
$\beta(EPOPAT) > 0$	$\beta(HTEPOPAT) > 0$	$\beta(NHTEPOPAT) < 0$
$\beta(NATBORDER) < 0$	$\beta(EUBORDER) < 0$	

error structure, or (iii) by introducing spatial effects from GDP per capita (PPP) of neighboring regions, or (iv) by allowing other spatially lagging covariates in the regression (Arbia *et al.*, 2005; OECD, 2009a). However, it has been argued that spatial interdependence vanishes due to the incorporation of national dummy variables and other region-specific controls (regional typology) (Bräuninger and Niebuhr, 2005). The majority of spatial autocorrelation is assumed to originate from national characteristics and thus represents country-specific effects (Fingleton, 2003). This approach has also been proposed by, e.g., Bräuninger and Niebuhr (2005), Frenken and Hoekman (2006), Paas and Schlitte (2007, 2008) and Falk and Sinabell (2008). Accordingly, the major fraction of spatial spillovers is considered to stop at national borders, meaning that intra-national interdependence and macroeconomic factors appear to be more influential.

The most distinct feature of the spatial regressions (section 5.4.4) is that spatial LM tests turn out to be insignificant and the hypothesis of no spatial dependence cannot be rejected as soon as national dummy variables (CTRYDUMMY) and regional controls (METRO, URBAN, CAPITAL) are introduced as they capture country-specific and region-specific effects.[506] Moreover, it seems that the OECD TL3 classification reduces spatial interdependence (OECD, 2010). In opposition, higher spatial aggregates are considered to generally induces an averaging process which reduces variance (Arbia *et al.*, 2005; Dewhurst and McCann, 2007; Arbia and Petrarca, 2010).[507]

5.4.3.2. Regional Growth in the EU-15

Table 5.6 summarizes regression models for the EU-15 group (645 observations), which include different covariates/ dummy variables (models 18-24). The results are quite similar to Frenken and Hoekman (2006), although they studied NUTS3 regions.[508]

In the first EU-15 regression, (model 18, OLS-R), the initial GDP per capita level is significant and negative (i.e., indicating convergence tendencies). The urbanization dummy (URBAN) is significant and positive in almost all regression alternatives (models 18-21). This is also the case with the alternative regional classifications, i.e., metro regions (METRO) (see model 20). Moreover, industry employment (INDUSTRY) is significant and negative, meaning that regions with high employment shares in the industry sector have lower growth rates (models 18-24).[509] This may be explained by the fact that production (and industry employment) is generally located in industry areas and neighboring regions but not in the highly populated centers, which represents a sort of urban hierarchy (Fujita and Ishii, 1999). Nevertheless, the results are generally in line with recent OECD studies at the higher TL2 regional level (1995-2005) (OECD, 2009b,a,f). An always significant covariate

[506] Regional time-invariant dummy variables are considered to introduce additional spatial heterogeneity and to make spatial dependence vanishing as similarity between observations is decreasing.

[507] To put it differently, the correlations between observations are assumed to increase with the size of the region, which leads to a severe loss in variation due to aggregation and averaging (i.e., the MAUP).

[508] Refer also to similar results presented in Geppert and Stephan (2008) and OECD (2009a). Nevertheless, the subsequent regressions differ significantly as they are done at the TL3 level and include differing covariates, e.g., a regional typology, EPO patent applications densities and employment controls.

[509] This result is identical to the reported negative coefficient of manufacturing concentration in OECD (2009a).

in the EU-15 regressions is the number of EPO patent applications per million inhabitants in high-technology (HTEPOPAT, models 18-22 and model 24). Non-high-technology EPO patenting (NHTEPOPAT), however, is insignificant in the EU-15 regressions (models 18-24). The regressions also include overall EPO-patenting activity (EPOPAT). It is significant and positive (model 23), which is in line with results reported in (OECD, 2009a).[510] Regional employment in services (SERVICES) is insignificant. Moreover, the internal border dummy (NATBORDER) and the external border dummy (EUBORDER) are not significant, although they show the expected negative sign.[511] Similarly, neither the capital region dummy (CAPITAL) nor the intermediate region dummy (INTERMEDIAT) are significant in the EU-15 regressions. The insignificance of the capital region dummy in the EU-15 group may be explained by the fact that non-capital EU-15 regions are, on average, on a similar level of development compared to capital regions but on a higher level of development compared to their NMS counterparts (see also the results reported in chapters 3 and 4). Moreover, the inequality decomposition and descriptive statistics have pointed to the possibility that EU-15 regions show lower variation in growth rates compared to the group of NMS countries. In regression model 19, which is again a regression with White heteroscedasticity-consistent standard errors, the regional typology (dummy for urban and intermediate areas) is replaced by a new covariate, i.e., population density (POPDENSITY), which is significant and positive. Industry employment and the initial GDP per capita level remain significant with similar point estimates and signs. In regression model 20, population density (POPDENSITY) is replaced by the metro region dummy (METRO), which is significant and positive. The intermediate region dummy (INTERMEDIAT) is significant and negative in almost all regressions (or at least insignificant), meaning that intermediate regions do not show higher growth rates. Finally, in model 24, high-technology patenting (HTEPOPAT) and the urban dummy (URBAN) are significant and positive.

It can be concluded from the different regression models, i.e., (i) Huber-White robust-sandwich estimator, (ii) robust HC3 regressions, (iii) cluster-robust regression with intra-group correlations, that population density, the regional typology and EPO patent applications are in most cases significant and positive.[512] On the other hand, the initial level of regions' GDP and the share of regions' industry employment are both significant but negative in all EU-15 regressions.[513] Moreover, the EU-15 regressions demonstrate that the capital region dummy (CAPITAL) is in all cases insignificant (models 18-24), meaning that capital regions in the EU-15 do not grow faster - at least according to the presented regressions. The negative sign of the GDP per capita level in the EU-15 regressions supports the widely accepted opinion that EU-15 regions are generally converging (Frenken and Hoekman, 2006; Paas and Schlitte, 2008). Although the regressions have not explicitly controlled for human capital, i.e., secondary and tertiary education, it may be the

510 Even the point estimate is quite similar in OECD (2009a), although the regressions are not directly comparable due to a different spatial classification system.

511 Döring *et al.* (2008) discussed similar results for growth regressions in Germany.

512 Results of (ii) and (iii) are available upon request.

513 The results at the TL3 level seem to be generally in line with findings of other studies at the NUTS3, TL2 and NUTS2 level. Refer to Niebuhr and Schlitte (2004), Bräuninger and Niebuhr (2005), Frenken and Hoekman (2006), Döring *et al.* (2008), Geppert and Stephan (2008), Paas and Schlitte (2008), Petrakos and Artelaris (2009) and Crespo Cuaresma *et al.* (2009b).

case that the regional typology (urban, metro) and EPO patenting activity have implicitly controlled for these factors. Furthermore, even if the assumption of independence of the observations is relaxed and observations are allowed to be correlated (e.g., intragroup-cluster correlations), the covariates show the same signs and similar significance levels.[514] Finally, concerning the significance of country dummy variables, the regressions clearly demonstrate that most EU-15 countries (and their regions) show stable development (growth) paths relative to the reference nation which is the United Kingdom (exceptions are Greece and Portugal).[515]

5.4.3.3. Regional Growth in the New Member States

After the presentation of the EU-15 regressions in the previous section, emphasis is now placed on the NMS.[516] The capital region dummy is assumed to be significant and positive, as growth is assumed to take place predominantly in metropolises and capital regions (see also chapter 5, section 5.3). The urban region dummy (URBAN) is assumed to be significant and positive. Table 5.7 summarizes the estimations for the NMS group and covers several covariates (models 25-31). The first NMS regression (model 25) shows a significant and positive capital region dummy (CAPITAL), meaning that capital regions in the NMS regions are generally equipped with higher growth rates. The initial GDP per capita level (GDPLEVEL) is, on average, not significant in these regressions (models 25-31), which points to missing convergence within the NMS group. Moreover, in opposition to the previously presented EU-15 regressions, the regional industry employment share (INDUSTRY) is significant and positive. Interestingly, the level of EPO patent applications per million inhabitants in non-high-technology fields (NHTEPOPAT) is significant and positive, which is in contrast to the EU-15 regression results. The next regression (model 26) replaces the standard regional typology (URBAN, INTERMEDIAT, RURAL) with population density (POPDENSITY), which ranges from low values in rural areas to very high values in metropolises and capital regions. Again, this density control is significant and positive (models 26 and 28). Besides that, the other covariates remain significant with similar coefficients as in the previous estimations. In the following regression (model 27), the population density control is replaced by the metro region dummy (METRO). METRO is significant and positive, which means that metro regions show on average higher annual regional growth rates. The regressions confirm that highly populated areas (CAPITAL, METRO) show, on average, higher growth rates. Finally, the subsequent regression (model 28) contains the metro region dummy (METRO) and the population density (POPDENSITY). Both coefficients are significant and positive, meaning that highly populated regions exhibit higher growth rates.[517] The other covariates remain significant with the same sign. Again, the capital region control dummy (CAPITAL) is significant at the 1% level (as it is the case with all alternative NMS regressions).

[514] The clustering assumption (OLS-C) relaxes the necessity of independence of observations as it only requires that the observations have to be independent across the clusters (groups), which are national units (CTRYDUMMY).

[515] Refer also to Geppert and Stephan (2008), although their study was conducted at the NUTS1/2 level (only 160-200 regions). See also Frenken and Hoekman (2006) for NUTS3 regressions.

[516] Malta is excluded due to data constraints regarding covariates.

[517] However, the two seem to be partially correlated.

Table 5.6. Robust regression for EU-15 regions

Model	(18) OLS-R EU-15	(19) OLS-R EU-15	(20) OLS-R EU-15	(21) OLS-R EU-15	(22) OLS-C EU-15	(23) OLS-C EU-15	(24) OLS-C EU-15
dep. var.: $1/Tln(y_{i,T}/y_{i,t})$							
GDPLEVEL	-0,0091***	-0,0092***	-0,0079***	-0,0081***	-0,0083***	-0,0086***	-0,0089***
	(0,0021)	(0,0021)	(0,0018)	(0,0017)	(0,0023)	(0,0024)	(0,0027)
NATBORDER	-0,0008	-0,0007	-0,0006				
	(0,0006)	(0,0006)	(0,0006)				
EUBORDER	-0,0008	-0,0008	-0,0004				
	(0,0018)	(0,0013)	(0,0013)				
INDUSTRY	-0,0051**	-0,0054**	-0,0067***	-0,0070***	-0,0068**	-0,0073**	-0,0051
	(0,0021)	(0,0021)	(0,0015)	(0,0013)	(0,0031)	(0,0033)	(0,0037)
SERVICES	0,0057	0,0048					0,0050
	(0,0043)	(0,0043)					(0,0056)
CAPITAL	0,0011	0,0008	0,0014			0,0014	0,0013
	(0,0018)	(0,0018)	(0,0019)			(0,0014)	(0,0014)
URBAN	0,0020*			0,0026***			0,0023**
	(0,0010)			(0,0008)			(0,0008)
INTERMEDIAT	-0,0004		-0,0014**				
	(0,0008)		(0,0006)				
METRO			0,0015**				
			(0,0007)				
POPDENSITY		0,0008**			0,0010***	0,0010***	
		(0,0004)			(0,0003)	(0,0002)	
HTEPOPAT	0,0010**	0,0010*	0,0010**	0,0011***	0,0010*		0,0010*
	(0,0005)	(0,0004)	(0,0005)	(0,0004)	(0,0005)		(0,0005)
NHTEPOPAT	0,0001	0,0001	0,0002				
	(0,0005)	(0,0005)	(0,0005)				
EPOPAT						0,0007*	
						(0,0003)	
AT	-0,0021	-0,0021	-0,0041**	-0,0032**	-0,0030***	-0,0037***	-0,0025
	(0,0018)	(0,0018)	(0,0015)	(0,0015)	(0,0008)	(0,0006)	(0,0015)
BE	-0,0076***	-0,0072***	-0,0078***	-0,0079***	-0,0074***	-0,0077***	-0,0079***
	(0,0016)	(0,0017)	(0,0016)	(0,0016)	(0,0004)	(0,0004)	(0,0005)
DE	-0,0060***	-0,0060***	-0,0069***	-0,0063***	-0,0062***	-0,0061***	-0,0061***
	(0,0013)	(0,0013)	(0,0013)	(0,0012)	(0,0007)	(0,0007)	(0,0008)
DK	-0,0030*	-0,0030*	-0,0043***	-0,0035**	-0,0034***	-0,0038***	-0,0035***
	(0,0017)	(0,0017)	(0,0015)	(0,0015)	(0,0004)	(0,0002)	(0,0004)
ES	0,0122***	0,0126***	0,0111***	0,01151***	0,0121***	0,0121***	0,0118***
	(0,0016)	(0,0016)	(0,0015)	(0,0013)	(0,0014)	(0,0015)	(0,0015)
FI	0,0051***	0,0067***	0,0037**	0,0045***	0,0062***	0,0061***	0,0048***
	(0,0019)	(0,0020)	(0,0017)	(0,0016)	(0,0010)	(0,0009)	(0,0010)
FR	-0,0050***	-0,0048***	-0,0057***	-0,0050***	-0,0048***	-0,0051***	-0,0050***
	(0,0011)	(0,0016)	(0,0010)	(0,0011)	(0,0006)	(0,0004)	(0,0007)
GR	-0,0004	-0,0003	-0,0032	-0,0030	-0,0027**	-0,0025*	-0,0014
	(0,0050)	(0,0050)	(0,0044)	(0,0042)	(0,0011)	(0,0013)	(0,0022)
IE	0,0292***	0,0300***	0,0273***	0,02874***	0,0294***	0,0292***	0,0291***
	(0,0292)	(0,0040)	(0,0039)	(0,0039)	(0,0011)	(0,0013)	(0,0016)
IT	-0,0108***	-0,0110***	-0,0115***	-0,0117***	-0,01165***	-0,0117***	-0,0112***
	(0,0014)	(0,0014)	(0,0012)	(0,0012)	(0,0008)	(0,0008)	(0,0011)
LU	0,02513***	0,0247***	0,0227***	0,0252***	0,0247***	0,0227***	0,0241***
	(0,0025)	(0,0025)	(0,0023)	(0,0018)	(0,0016)	(0,0011)	(0,0010)
NL	0,0034***	0,0035***	0,0029***	0,0029**	0,0031***	0,0032***	0,0031***
	(0,0034)	(0,0013)	(0,0011)	(0,0012)	(0,0006)	(0,0006)	(0,0007)
PT	0,0049	0,0048	0,0030	0,0029	0,0031	0,0037	0,0044
	(0,0030)	(0,0030)	(0,0022)	(0,0029)	(0,0020)	(0,0025)	(0,0029)
SE	-0,0056***	-0,0042**	-0,0066***	-0,0059***	-0,0042***	-0,0044***	-0,0058***
	(0,0015)	(0,0016)	(0,0013)	(0,0013)	(0,0008)	(0,0006)	(0,0006)
N	645	645	645	645	645	645	645
R-squared	0,5592	0,5583	0,5562	0,5551	0,5554	0,5556	0,5576

Source: own estimations. *Notes:* EU-15 growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; OLS-R represents the Huber and White robust-sandwich estimator/robust estimator of variance; OLS-C represents cluster-robust regression with intragroup correlation; constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is UK and RURAL for settlement type dummy.

To conclude, the conditional convergence regressions for the NMS group support several of the proposed hypotheses: (i) the capital region dummy (CAPITAL) is significant and positive; (ii) the metro region dummy (METRO) and population density (POPDENSITY) are significant and positive; (iii) industry employment (INDUSTRY) is significant and positive in the NMS group, which is different to the EU-15 regressions; (iv) the control for non-high-technology EPO patent applications (NHTEPOPAT) is significant and positive; (v) the initial level of GDP per capita (GDPLEVEL) is not significant, meaning that the NMS group shows divergence, which is in strong contradiction to the EU-15 case.[518] Population density seems to be positively related but urban and metro regions in particular exhibit higher growth rates in the EU-15 group. This finding could be explained by the fact that densely populated areas have on average higher levels and growth rates of productivity, a larger stock of human capital and a higher technology level, which has been demonstrated in terms of EPO patenting activity (see chapter 3, section 3.5); cities and metropolises can be regarded as the pivotal growth poles and centers of the creation and diffusion of knowledge and new ideas.[519] That being the case, the aforementioned results can be interpreted as preliminary evidence for higher growth rates in urban regions, metropolises and capital regions in the NMS. In the EU-15, the capital dummy is not significant, which could be explained by the fact that core-periphery structures in the EU-15 are less pronounced.

A serious shortcoming of the presented empirical analysis is the lack of an exploration and test of the working channels of agglomeration economies and missing research results on causalities, endogeneity and additional covariates. Moreover, time-invariant covariates, persistent data constraints and potential spatial autocorrelation have prevented the application of standard panel estimators.

5.4.4. European Regional Growth and Spatial Spillovers

5.4.4.1. A General Spatial Model

Capturing spatial interdependence between observations in regression analysis avoids severe statistical problems, e.g., unstable parameters, unreliable inference. Moreover, it provides information on spatial relationships between observations (e.g., regions). Depending on the specific technique, spatial relationships can be implemented into regression models in various forms; i.e., as a relationship between a dependent and independent variable, between the dependent variable and a spatial lag of itself, or via the error term (Anselin, 2006; OECD, 2009a; Andersson and Gråsjö, 2009).[520]

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518 This result has also been confirmed by the studies of Bräuninger and Niebuhr (2005, 2008), Paas and Schlitte (2008), Petrakos and Artelaris (2009) and Crespo Cuaresma *et al.* (2009b), although the studies have been conducted at a different spatial level of aggregation.

519 For similar results refer to Williamson (1965), Florida (1995), Fujita and Thisse (1996), Duranton and Puga (2001), Szörfi (2007) and Crespo Cuaresma *et al.* (2010).

520 See also Anselin (1988a), Anselin (1992), Anselin and Florax (1995), Anselin and Bera (1998) and Anselin (1999).

Table 5.7. Robust regression for NMS

Model	(25) OLS-R NMS	(26) OLS-R NMS	(27) OLS-R NMS	(28) OLS-R NMS	(29) OLS-C NMS	(30) OLS-C NMS	(31) OLS-C NMS
dep. var.: $1/Tln(y_{i,T}/y_{i,t})$							
GDPLEVEL	-0,0052	-0,0078	0,0020	-0,0059	-0,0052	0,0020	-0,0002
	(0,0066)	(0,0060)	(0,0042)	(0,0062)	(0,0076)	(0,0039)	(0,0069)
NATBORDER	-0,0037*	-0,0036*	-0,0034*	-0,0037*	-0,0037	-0,0034	
	(0,0021)	(0,0021)	(0,0019)	(0,0020)	(0,0036)	(0,0029)	
EUBORDER	-0,0031	-0,0021	-0,0024	-0,0018	-0,0031	-0,0024	
	(0,0021)	(0,0020)	(0,0020)	(0,0020)	(0,0019)	(0,0019)	
INDUSTRY	0,0114**	0,0119**	0,0103*	0,0106*	0,0114*	0,0103	0,0131**
	(0,0056)	(0,0060)	(0,0055)	(0,0058)	(0,0059)	(0,0061)	(0,0056)
SERVICES	0,0075	0,0050		0,0020	0,0075		
	(0,0080)	(0,0072)		(0,0074)	(0,0089)		
CAPITAL	0,0225***	0,0119***	0,0194**	0,0199***	0,0225***	0,0195***	0,0248***
	(0,0034)	(0,0060)	(0,0036)	(0,0033)	(0,0026)	(0,0035)	(0,0029)
URBAN	0,0065				0,0065		0,0064
	(0,0050)				(0,0037)		(0,0029)
INTERMEDIAT	0,0006		-0,0015		0,0006	-0,0015	
	(0,0022)		(0,0020)		(0,0028)	(0,0029)	
METRO			0,0058***	0,0036*		0,0058***	
			(0,0019)	(0,0020)		(0,0013)	
POPDENSITY		0,0037***		0,0032**			
		(0,0010)		(0,0011)			
HTEPOPAT	-0,0087	-0,0079*	-0,0097*	-0,0084	-0,0087	-0,0097	
	(0,0056)	(0,0055)	(0,0056)	(0,0055)	(0,0049)	(0,0059)	
NHTEPOPAT	0,0047**	0,0038*	0,0050**	0,0038*	0,0047**	0,0050**	
	(0,0021)	(0,0021)	(0,0022)	(0,0021)	(0,0018)	(0,0019)	
CY	-0,0262***	-0,0228***	-0,0313***	-0,0254***	-0,0262***	-0,0313***	-0,0318***
	(0,0072)	(0,0066)	(0,0061)	(0,0068)	(0,0053)	(0,0042)	(0,0048)
CZ	-0,0255***	-0,0251***	-0,0290***	-0,0261***	-0,0255***	-0,0290***	-0,0255***
	(0,0044)	(0,0039)	(0,0037)	(0,0039)	(0,0032)	(0,0019)	(0,0031)
EE	0,0278***	0,0314***	0,0315***	0,0316***	0,0278***	0,0315***	0,0272***
	(0,0055)	(0,0055)	(0,0056)	(0,0055)	(0,0030)	(0,0017)	(0,0035)
HU	-0,0105**	-0,0104***	-0,0103***	-0,0102**	-0,0104***	-0,0102***	-0,0084***
	(0,0043)	(0,0039)	(0,0038)	(0,0039)	(0,0030)	(0,0022)	(0,0009)
LT	0,0094*	0,0109**	0,0098**	0,0102**	0,0094**	0,0098**	0,010***
	(0,0049)	(0,0047)	(0,0049)	(0,0047)	(0,0029)	(0,0030)	(0,0030)
LV	0,0134*	0,0149**	0,0174**	0,0154**	0,0134**	0,0174***	0,0163**
	(0,0077)	(0,0070)	(0,0068)	(0,0070)	(0,0055)	(0,0042)	(0,0051)
PL	-0,0093**	-0,0109***	-0,0111***	-0,0125***	-0,0093*	-0,0111**	-0,0069**
	(0,0040)	(0,0038)	(0,0039)	(0,0037)	(0,0042)	(0,0042)	(0,0021)
SI	-0,010*	-0,0090*	-0,0155***	-0,0098*	-0,0105***	-0,0155***	-0,0092**
	(0,0060)	(0,0054)	(0,0047)	(0,0052)	(0,0029)	(0,0024)	(0,0048)
N	121	121	121	121	121	121	121
R-squared	0,7549	0,7661	0,7601	0,7713	0,7549	0,7601	0,7248

Source: own estimations. *Notes:* NMS growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; OLS-R represents the Huber-White robust-sandwich estimator/robust estimator of variance; OLS-C represents cluster-robust regression with intragroup correlation; constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is SK and RURAL regions for settlement type dummy.

A "general" spatial model that incorporates several spatially lagged variables but also spatially correlated error terms can be expressed as in 5.4.3:

$$\begin{aligned} y &= \underbrace{\rho W_y y}_{a} + \underbrace{\beta X}_{b} + \underbrace{\varphi W_X X}_{c} + \varepsilon, \\ \varepsilon &= \underbrace{\lambda W_\xi \xi}_{d} + u, \\ u &\sim N(0, \sigma_u^2 I). \end{aligned} \tag{5.4.3}$$

W represents a spatial weight matrix for the autoregressive process $\rho W_y y$, the cross-regressive process $\varphi W_X X$ and the error term process $\lambda W_\xi \xi$. y represents a $(n \times 1)$ vector of observations of a dependent variable; Wy is a $(n \times 1)$ vector of observations of a spatially lagged dependent variable for a $(n \times n)$ spatial weight matrix W; ρ represents the $(k \times 1)$ spatial auto-regressive parameter/coefficient; X is the $(n \times k)$ vector of exogenous explanatory variables; β is a $(k \times 1)$ vector of corresponding coefficients; $\varphi W_X X$ represents a $(n \times 1)$ vector of a spatially lagged independent variable. ε finally represents a $(n \times 1)$ vector of independent disturbances, which can be implemented as a spatially lagged process. u is a $(n \times 1)$ vector of errors assumed to be independently and normally distributed with $u \sim N(0, \sigma_u^2 I)$. The generalized spatial model can also be reduced to several sub-mechanisms a, b, c, d. Note that a represents an autoregressive process of the dependent variable, whereas c represents a cross-regressive process. d is a spatially weighted process of the error term; b is just a standard vector of exogenous explanatory variables (Freund, 2008; Richter and Freund, 2008; Andersson and Gråsjö, 2009). Thus, alternative implementations $[0; 1]$ of weights (W_y, W_X, W_ξ) will provide differing model structures that account for alternative forms of spatial interdependence. Simple spatial lags are obtained by setting $W_\xi = 0$, so that the error term satisfies classical assumptions (Freund, 2008; Richter and Freund, 2008; Andersson and Gråsjö, 2009).

5.4.4.2. Regional Growth Models and Spatial Interdependence

The previous section stressed general methodological issues of spatial dependence with respect to regional regressions. Potential issues in cross-sectional regional data and regressions can be addressed by spatial models, e.g., commuting effects, trade flows, input-output structures, diffusion of knowledge and technology across regional borders (Bräuninger and Niebuhr, 2005; Arbia *et al.*, 2008; Patuelli *et al.*, 2010).[521] However, allowing for spatial spillovers in growth regressions could lead to decreasing effects of the initial GDP level on the growth rate and thus on the speed of convergence (Abreu *et al.*, 2005; Paas and Schlitte, 2008; Geppert and Stephan, 2008). If spatial spillovers are significant, then European regions are considered to influence neighboring regions' growth rates in a meaningful and positive (or negative) way (and vice versa). Moreover, the presence of spatial growth spillovers could be interpreted in the following way: exogenous shocks in one region, e.g., supply and/or demand shocks, or knowledge accumulation, induce positive (negative) effects on neighboring regions and some kind of feed-back effects as spatial dependence is

[521] See also Rey and Montouri (1999) and Baumont *et al.* (2000).

bi-directional.[522] In the same vein, policy instruments with local focus would also be determined by a sincere spatial crowding-out effect to neighboring units (Abreu *et al.*, 2005; Freund, 2008; Harris, 2008).

The incorporation of spatially lagged dependent variables or errors leads to endogeneity issues. Anselin (1988a), among others, proposed a spatial maximum-likelihood approach.[523] Accordingly, the first methodological line of research implements spatial interaction via the dependent variable by modeling the spatial processes of interest (see model 5.4.3) (Anselin, 1988a, 2002, 2006). Otherwise, OLS estimates would be biased, if substantial spatial dependence is present. A second approach identifies spatial dependence between ignored variables, which is reflected by the error term (see model 5.4.3). Such nuisance spatial dependence yields unbiased but inefficient OLS regression results (Anselin, 1988a, 2002, 2006; Fingleton and López-Bazo, 2006).[524] To repeat a point made earlier, spatial growth models that explicitly account for spatial autocorrelation (see section 4.2.1.4) show in most cases slower catching-up processes because the point estimates of the initial income variable (GDPLEVEL) decrease due to the implementation of a spatially lagged dependent variable (Rey and Montouri, 1999; Harris, 2008; Arbia *et al.*, 2008).[525]

Regarding regional heterogeneity, the applied spatial typology (i.e., capital, urban, rural regions) and the implementation of national dummy variables control for a large fraction of spatial interdependence between areas, but may, nevertheless, leave considerable variation in the data. Under this hypothesis, the majority of spatial spillovers are unlikely to reach beyond regions' borders (Bräuninger and Niebuhr, 2005; Andersson and Gråsjö, 2009; Patuelli *et al.*, 2010).[526] However, in order to test for remaining neighborhood effects, the growth models have to test for nuisance and substantive spatial dependence by inclusion of (i) an endogenous $(n \times n)$ spatially lagged $(k \times 1)$ vector of dependent variables $(\rho W y)$, or (ii) by a $(n \times n)$ spatially lagged $(k \times 1)$ vector of exogenous variables $(\phi W X)$, or (iii) by inclusion of potential spatial interaction in the error term $(\lambda W \varepsilon)$ (Anselin, 2006; Andersson and Gråsjö, 2009), or (iv) by inclusion of additional covariates that minimize spatial dependence (regional typology or spatial filter) (Anselin, 2006; Andersson and Gråsjö, 2009).[527]

522 It is incorrect to compare the β-coefficient of a spatial lag model (direct marginal effect) with the $\beta-$coefficient of an OLS regression (total marginal effects). The column sum of the matrix of the spatial multiplier $\beta(1-\rho W)^{-1}$ then captures the total effect of an exogenous shock from region i on all neighboring regions j, whereas the row sum of the matrix represents the total effect on region i from a simultaneous shock in all neighboring regions j (Abreu *et al.*, 2005).

523 Spatial ML-regressions allows for endogeneity and heteroscedasticity. For more details see, e.g., Anselin (1992), Anselin and Getis (1992), Rey and Montouri (1999), Anselin (1999), Smirnov and Anselin (2001), Abreu *et al.* (2005), van Oort and Raspe (2007), Anselin (2007) and Arbia *et al.* (2008).

524 The Moran's I test offers results for alternative forms of ignored spatial dependence, whereas the LM test supplies detailed information about the kind of spatial dependence (Anselin and Rey, 1991; Anselin and Bera, 1998; Anselin and Florax, 1995). It is clear that the choice of spatial weights and the modeled distance decay effects are highly dependent on the assumed spatial process.

525 See also Abreu *et al.* (2005) and Fingleton and López-Bazo (2006).

526 The inclusion of spatial spillovers do not at all give any theoretic indication about the microeconomic or regional origin of the spillover. The spatial control variable is simply considered to be a necessary econometric correction.

527 Spatial dependence is of nuisance form if the LM-test for spatial error dependence (LM_{err}) is more significant than the test for spatial lag dependence (LM_{lag}) and the robust LM test for the error (RLM_{err}) is significant and the one for the robust spatial lag is not (RLM_{lag}). Contrary, when the

In this respect, the regional typology can be interpreted to reduce spatial dependence between observations.[528]

A first possible treatment of spatial effects that might affect inter-regional growth rates is accomplished by incorporating a $k \times 1$ vector of spatially weighted exogenous variables, $WX_{i,t}$, with

$$W = \begin{cases} w_{ij} = 1, & \text{if } d_{ij} \leq d \\ w_{ij} = 0, & \text{otherwise.} \end{cases} \tag{5.4.4}$$

w_{ij} defines the interaction between regions i and j; W is a spatial $n \times n$ weight matrix. The weight matrix combines a spatial structure (distance band with $d_{ij} \leq d$) with a $k \times 1$ vector of regional factors ($X_{i,t}$) of neighboring regions with a parameter vector ϕ (see section 4.2.1.3 for more details). Therefore, the original growth regression model (5.4.2), which represents a log-linear approximation of a conditional convergence equation, can be extended by incorporating spatial spillover effects from neighboring regions, i.e., $Wln(X_{i,t})$, which transforms the initial a-spatial conditional convergence model to a cross-regressive spatial convergence model (SCR). Thus, spatially lagged income levels attribute importance to spatial relations (Abreu *et al.*, 2005; Anselin, 2006; Andersson and Gråsjö, 2009).[529]

$$\begin{aligned} \frac{1}{T} ln\left(\frac{y_{t+T}}{y_t}\right) &= \beta_0 + \beta_1 ln(y_t) + \beta_2 ln(X_t) + \phi\left[Wln(X_t)\right] + \varepsilon \\ &\varepsilon \sim N(0, \sigma_\varepsilon^2 I) \end{aligned} \tag{5.4.5}$$

The spatial (mixed-regressive-) autoregressive model (SAR) with inter-regional spillovers effects represents an alternative (5.4.6). It is different to the previous model (5.4.5) as it includes a spatial lag of the dependent variable ($\sum_{j=1}^{N} w_{ij} \frac{1}{T} ln\left(\frac{y_{j,t+T}}{y_{j,t}}\right)$). However, the problem arises that the spatial lag is endogenous to the dependent variable, which requires 2SLS- or ML-technique (Anselin and Rey, 1991; Anselin, 2006; Andersson and Gråsjö, 2009).

$$\begin{aligned} \frac{1}{T} ln\left(\frac{y_{t+T}}{y_t}\right) &= \beta_0 + \beta_1 ln(y_t) + \beta_3 ln(X_t) + \rho\left[\frac{1}{T} Wln\left(\frac{y_{t+T}}{y_t}\right)\right] + \varepsilon \\ &\varepsilon \sim N(0, \sigma_\varepsilon^2 I) \end{aligned} \tag{5.4.6}$$

W represents the spatial weight matrix for the autoregressive process. In general, $\sum_{j=1}^{N} w_{ij} y_j$ is a $(n \times 1)$ vector of a spatially lagged dependent variable, here $\frac{1}{T} ln\left(\frac{y_{j,t+T}}{y_{j,t}}\right)$ for a $n \times n$ spatial weight matrix; ρ represents the parameter vector of the spatial auto-regressive process

robust spatial lag LM-test (RLM_{lag}) is significant, inference goes in favor of a spatial autocorrelated lag variable. Alternative treatment of spatial weights will provide differing model structures that account for alternative spatial mechanisms (Anselin and Florax, 1995; Andersson and Gråsjö, 2009).

528 See Rey and Montouri (1999), Baumont et al. (2001, 2003), Le Gallo et al. (2003), Anselin (2006) and Patuelli et al. (2010), among others.

529 This specification can still be estimated with an OLS estimator as $\sum_{j=1}^{N} w_{ij} X_{j,t}$ is exogenous to the covariates as long as the errors and the dependent variables are independent.

(Anselin, 2006; Andersson and Gråsjö, 2009).[530] If the spatially lagged (weighted) dependent variable is positive and significant, it would mean that (i) spatial spillovers exist and (ii) that spillovers are determining the growth process of neighboring regions.

As an alternative to the above presented SAR model, the so-called spatial error model (SER) is adequate when nuisance spatial dependence originates from omitted variables (Andersson and Gråsjö, 2009).[531] When the errors follow a first order process, the conditional convergence/growth model can be written as in 5.4.7:

$$\begin{aligned} \frac{1}{T} ln\left(\frac{y_{t+T}}{y_t}\right) &= \beta_0 + \beta_1 ln(y_t) + \beta_3 ln(X_t) + \varepsilon \\ &\quad \varepsilon = \lambda W \xi + u \\ &\quad u \sim N(0, \sigma_u^2 I) \end{aligned} \tag{5.4.7}$$

Thus, the SER model includes spatial dependence in the error term.[532]

A technical consideration concerns the choice between the above illustrated regression approaches. Following the arguments of, e.g., Fingleton (2003), growth spillovers are likely to cross regions' administrative borders and might influence neighboring regions' growth process (Bräuninger and Niebuhr, 2005). The growth regressions are done for the EU-15 and NMS regions.[533] For illustration and comparison purpose, the SAR estimations are reported for the EU-15 and NMS group.

5.4.4.3. Estimation Results

With regard to the methodological issues discussed in the previous section, tables 5.8 and 5.9 (and B.11, appendix) highlight the regression results for the EU-15 group (models 32-40). The regression results for the NMS group (models 40-53) are illustrated in table 5.10 (and B.12, appendix).

It can be concluded from the highlighted EU-15 regressions (models 32-45) that regional spillovers (of average annual regional GDP growth rates) are only statistically significant when country dummy variables (CTRYDUMMY) are excluded from the regressions (see table B.11, appendix, models 41-45). As soon as country dummy variables are included (models 32-40), the spatial multipliers cannot reject the hypothesis of no spatial dependence. Rook contiguity distance matrices (rook1, rook12) and a large number of alternative

530 It represents the spatially weighted average growth rate of neighboring observations that influences region i. See also Anselin and Bera (1998) and Rey and Montouri (1999).

531 The issue is treated by the error process with errors from different neighboring regions (displaying spatial covariance).

532 λ is a scalar spatial error coefficient expressing the intensity of spatial correlation between regression residuals ε. $u_{t,1}, u_{t,2}, ..., u_{t,n}$ is assumed to be independently and normally distributed. SER and SAR are in general estimated in a maximum likelihood (ML) or generalized method of moments (GMM) framework (Anselin, 1988a, 2006; Andersson and Gråsjö, 2009).

533 The robust LM-lag and robust LM-error test have been applied to choose between the SER and SAR concept. It turns out that LM-lag is always larger than LM-error. However, all LM-tests remain insignificant when country dummy variables are included.

distance band weight matrices (e.g., 100, 200, 250, 300, 350, 400, 500 kilometers) have been tested.[534]

According to the theoretical remarks on knowledge diffusion and inter-regional effects (chapter 2, section 2.1) and the empirical evidence of existing studies (chapter 2, section 2.2), spatial interdependence with significant and positive influence (lag or error interdependence) is expected to occur within a distance band of maximum 200-400 kilometers as has been observed in several regional studies (Moreno *et al.*, 2005c; Greunz, 2005).[535] Spatial spillovers are most likely to happen in close neighborhoods or between primary and secondary growth poles at a proximate distance. However, the spatial LM-tests cannot confirm remaining spatial autocorrelation when national dummy variables (as well as regional typology dummy variables) are included (models 32-40). Therefore, national dummy variables are interpreted as a crucial factor in these models as they indicate that inter-regional spillovers seem to decrease (and vanish) at national borders.[536] Regional and national characteristics seem to play a dominant role compared to spatial spillovers; at least in the methodological approach used in this study. Thus, in the presented regressions (models 32-40), the effects of spatial spillovers seem to be sufficiently captured by national controls (and the implementation of a regional typology), which eliminate spatial autocorrelation as indicated by insignificant spatial lags in the spatial maximum likelihood set-up and insignificant spatial LM-tests (see also Eckey *et al.*, 2003; Fingleton, 2003; Bräuninger and Niebuhr, 2005). Concerning the covariates in the presented spatial model alternatives, GDPLEVEL is always significant and negative in the EU-15 group (tables 5.8 and 5.9, models 32-40), which can be interpreted as evidence for convergence of EU-15 regions. This finding is also supported by the work of Bräuninger and Niebuhr (2005, 2008) at the NUTS1/2 level. Moreover, similar to the previous OLS regressions (see section 5.4.3.2), the regional industry employment share (INDUSTRY) is significant and negative. URBAN and HTEPOPAT are again significant and positive. The spatial spillover, ρ, turns out to be statistically significant and positive, dominating other covariates, when national controls (CTRYDUMMY) are excluded (see table B.11, appendix, models 41-45). In this case (models 41-45), the capital region control (CAPITAL) becomes also significant and positive, whereas other covariates become insignificant.

The spatial regressions for NMS regions (models 46-53) are presented in the following (table 5.10 and table B.12, appendix). First and foremost, the results are quite similar compared to the a-spatial approach in the previous section 5.4.3.3. It can be concluded from the ML-estimations (models 46-50) that capital regions (CAPITAL) exhibit higher growth rates (table 5.10). Moreover, industry employment (INDUSTRY) is significant and positive. The initial level of GDP per capita (GDPLEVEL) is insignificant when country dummy variables are included. However, when country dummy variables are excluded, the spatial lag becomes significant and positive, dominating other covariates (table B.12, models 51-53, appendix), meaning that spatial autocorrelation is present (i.e., spillovers).

[534] A fraction of all tested weight matrices is presented in the tables. Further information is available from the author upon request. For similar results at the NUTS1/2 level see Bräuninger and Niebuhr (2005).

[535] See also chapter 2, section 2.2.

[536] This idea has been proposed by Bräuninger and Niebuhr (2005) and Feldkircher (2006). Refer also to Geppert *et al.* (2005), Geppert and Stephan (2008) and Paas and Schlitte (2007, 2008) for similar conclusions with respect to national controls.

To conclude, regional industry employment (INDUSTRY), the urban dummy (URBAN) and capital dummy (CAPITAL) remain significant and positive in spatial NMS regressions. Interestingly, the GDP level (GDPLEVEL) becomes significant and negative when country dummy variables are excluded, which could be interpreted as convergence tendencies in case that regressions do not control for national characteristics.

To conclude, the presented simple regressions demonstrate that the EU-15 and NMS TL3 regions show differing growth structures. Moreover, the significance of covariates/ dummy variables in the regional growth regressions is not identical. The regional typology can be considered to implement additional information into the regional regressions. Furthermore, patenting activity, measured via EPO patent application densities, adds additional information regarding inventive activity into the regressions.[537] The reported results, although preliminary and limited in detail, seem to confirm the existence of structural differences between the NMS and EU-15 concerning the growth process of regions. Nevertheless, additional empirical analysis is needed in order to analyze the structural features and differences of the European regions. A necessary step would be to improve the availability of regional data at the TL3 level for the EU-25, Switzerland and Norway; e.g., employment data at the 2-3 digit-level, data on human resources and skill-levels, spatially disaggregated R&D data at the TL3 level (governmental R&D, higher-educational R&D, business R&D). Furthermore, the provision of longer time series on GDP and productivity at the TL3 level should improve the possibilities for future descriptive and econometric studies.

[537] Unfortunately, the causality remains unchallenged. Does patenting activity affect regional growth or vice versa? This issue needs additional research.

Table 5.8. Spatial regression (ML-SAR) for EU-15 regions

Model	(32) EU-15	(33) EU-15	(34) EU-15	(35) EU-15	(36) EU-15
dep. var.: $1/Tln(y_{i,T}/y_{i,t})$					
GDPLEVEL	-0,0095***	-0,0088***	-0,0088***	-0,0089***	-0,0091***
	(0,0016)	(0,0015)	(0,0016)	(0,0016)	(0,0016)
NATBORDER	-0,0008	-0,0008	-0,0007	-0,0008	-0,0008
	(0,0006)	(0,0006)	(0,0006)	(0,0006)	(0,0006)
EUBORDER	-0,0008	-0,0007	-0,0003	-0,0003	-0,0003
	(0,0013)	(0,0013)	(0,0013)	(0,0013)	(0,0013)
INDUSTRY	-0,0053**	-0,0050***	-0,0056***	-0,0056***	-0,0058***
	(0,0017)	(0,0016)	(0,0017)	(0,0017)	(0,0017)
SERVICES	0,0050	0,0062*	0,0046	0,0045	0,0044
	(0,0034)	(0,0033)	(0,0033)	(0,0033)	(0,0033)
CAPITAL	0,0012	0,0010	0,0013	0,0013	0,0012
	(0,0014)	(0,0014)	(0,0013)	(0,0013)	(0,0013)
URBAN	0,0020*	0,0019*	0,0017*	0,0017*	0,0017*
	(0,0010)	(0,0010)	(0,0010)	(0,0010)	(0,0010)
INTERMEDIAT	-0,0004	-0,0004	-0,0004	-0,0004	-0,0004
	(0,0008)	(0,0008)	(0,0008)	(0,0008)	(0,0008)
HTEPOPAT	0,0010**	0,0010**	0,0010*	0,0010**	0,0010**
	(0,0005)	(0,0004)	(0,0005)	(0,0005)	(0,0005)
NHTEPOPAT	0,0001	0,0002	0,0002	0,0001	0,0001
	(0,0005)	(0,0005)	(0,0005)	(0,0005)	(0,0005)
AT	-0,0022	-0,0018	-0,0023	-0,0030	-0,0039**
	(0,0014)	(0,0017)	(0,0018)	(0,0018)	(0,0019)
BE	-0,0077***	-0,0070***	-0,0074***	-0,0079***	-0,0086***
	(0,0020)	(0,0024)	(0,0023)	(0,0023)	(0,0023)
DE	-0,0061***	-0,0056***	-0,0058***	-0,0065***	-0,0074***
	(0,0092)	(0,0011)	(0,0012)	(0,0013)	(0,0013)
DK	-0,0028	-0,0026	-0,0029	-0,0036*	-0,0046**
	(0,0018)	(0,0021)	(0,0021)	(0,0022)	(0,0013)
ES	0,0124***	0,0117***	0,0121***	0,0127***	0,0135***
	(0,0013)	(0,0014)	(0,0016)	(0,0015)	(0,0016)
FI	0,0046***	0,0051***	0,0046**	0,0047**	0,0051***
	(0,0016)	(0,0019)	(0,0019)	(0,0019)	(0,0019)
FR	-0,0050***	-0,0047***	-0,0049***	-0,0055***	-0,0061***
	(0,0008)	(0,0010)	(0,0012)	(0,0012)	(0,0013)
GR	-0,0050	0,0004	-0,0010	-0,0016	-0,0021
	(0,0025)	(0,0027)	(0,0028)	(0,0027)	(0,0027)
IE	0,0281***	0,0284***	0,0282***	0,0295***	0,0306***
	(0,0023)	(0,0029)	(0,0032)	(0,0031)	(0,0030)
IT	-0,0110***	-0,0103***	-0,0105***	-0,0117***	-0,0132***
	(0,0010)	(0,0012)	(0,0017)	(0,0018)	(0,0019)
LU	0,0242***	0,0254***	0,0248***	0,0242***	0,0236***
	(0,0079)	(0,0076)	(0,0075)	(0,0075)	(0,0071)
NL	0,0032*	0,0035	0,0036	0,0029	0,0021
	(0,0019)	(0,0022)	(0,0022)	(0,0022)	(0,0022)
PT	0,0044**	0,0048**	0,0031	0,0033	0,0037*
	(0,0020)	(0,0021)	(0,0022)	(0,0022)	(0,0022)
SE	-0,0059***	-0,0051***	-0,0056***	-0,0062***	-0,0068***
	(0,0016)	(0,0019)	(0,0019)	(0,0019)	(0,0019)
ρ	-0,0517	0,0393	0,0412	-0,0519	-0,1727
	(0,0317)	(0,0342)	(0,0915)	(0,1026)	(0,1129)
N	640	640	640	640	640
W-matrix	$\vartheta : rook1$	$\vartheta : rook12$	$\vartheta : 250km$	$\vartheta : 300km$	$\vartheta : 350km$
LR-test	0,0006	1,2752	0,1893	0,2521	-71,2431
AIC	-4460,3	-4463,53	-4446,52	-4443,82	-4372,33
log likelihood	2256,15	2256,76	2248,2581	2247,91	2212,16
R-squared	0,5540	0,5601	0,5634	0,5635	0,5652

Source: own estimations. *Notes:* Growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; SAR-maximum likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags insignificant for tested threshold distances ϑ (contiguity, kilometers); constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is UK and rural regions for settlement type. Projected shapefile and matrix generated in ArcGIS 9.3.1. environment.

Table 5.9. Spatial regression (ML-SAR) for EU-15 regions (cont'd)

Model	(37) EU-15	(38) EU-15	(39) EU-15	(40) EU-15
dep. var.: $1/Tln(y_{i,T}/y_{i,t})$				
GDPLEVEL	-0,0089***	-0,0082***	-0,0091***	-0,0084***
	(0,0016)	(0,0015)	(0,0016)	(0,0015)
NATBORDER	-0,0007		-0,0007	
	(0,0006)		(0,0006)	
EUBORDER	-0,0003		-0,0003	
	(0,0013)		(0,0013)	
INDUSTRY	-0,0060***	-0,0069***	-0,0060***	-0,0070***
	(0,0016)	(0,0011)	(0,0016)	(0,0011)
SERVICES	0,0036		0,0035	
	(0,0033)		(0,0033)	
CAPITAL	0,0009		0,0009	
	(0,0014)		(0,0014)	
POPDENSITY	0,0010***	0,0010***	0,0009***	0,0010***
	(0,0003)	(0,0003)	(0,0003)	(0,0003)
HTEPOPAT	0,0009*	0,0009***	0,0009*	0,0009***
	(0,0005)	(0,0004)	(0,0005)	(0,0004)
NHTEPOPAT	0,0002		0,0001	
	(0,0005)		(0,0005)	
AT	-0,0021	-0,0028*	-0,0027	-0,0034**
	(0,0017)	(0,0016)	(0,0018)	(0,0017)
BE	-0,0070***	-0,0072***	-0,0075***	-0,0077***
	(0,0023)	(0,0023)	(0,0023)	(0,0023)
DE	-0,0056***	-0,0059***	-0,0063***	-0,0066***
	(0,0012)	(0,0012)	(0,0013)	(0,0013)
DK	-0,0027	-0,0032	-0,0035	-0,0039
	(0,0021)	(0,0020)	(0,0021)	(0,0021)
ES	0,0128***	0,0125***	0,0133***	0,0130***
	(0,0016)	(0,0015)	(0,0016)	(0,0015)
FI	0,0063***	0,0061***	0,0065***	0,0064***
	(0,0020)	(0,0019)	(0,0020)	(0,0019)
FR	-0,0046***	-0,0046***	-0,0052***	-0,0051***
	(0,0012)	(0,0012)	(0,0012)	(0,0012)
GR	-0,0009	-0,0026	-0,0014	-0,0030
	(0,0027)	(0,0022)	(0,0028)	(0,0022)
IE	0,0292***	0,0289***	0,0301***	0,0300***
	(0,0031)	(0,0031)	(0,0030)	(0,0029)
IT	-0,0106***	-0,0112***	-0,0110***	-0,0123***
	(0,0017)	(0,0016)	(0,0018)	(0,0017)
LU	0,0246***	0,0248***	0,0241***	0,0242***
	(0,0075)	(0,0073)	(0,0075)	(0,0074)
NL	0,0036	0,0033	0,0030	0,0027
	(0,0022)	(0,0022)	(0,0022)	(0,0022)
PT	0,0031	0,0016	0,0033	0,0019
	(0,0022)	(0,0016)	(0,0022)	(0,0017)
SE	-0,0040**	-0,0041**	-0,0045**	-0,0046**
	(0,0020)	(0,0020)	(0,0020)	(0,0020)
ρ	0,0002	0,0266	-0,0530	-0,0576
	(0,0005)	(0,0909)	(0,1020)	(0,1014)
N	640	640	640	640
W-matrix	$\vartheta : 250km$	$\vartheta : 250km$	$\vartheta : 300km$	$\vartheta : 300km$
LR-test	0,1360	0,0813	0,2626	0,3188
AIC	-4446,46	-4453,39	-4446,59	-4453,63
log likelihood	2248,23	2246,69	2248,29	2246,81
R-squared	0,5639	0,5618	0,5640	0,5620

Source: own estimations. *Notes:* Growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; SAR-maximum likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags insignificant for tested threshold distances ϑ (contiguity, kilometers); constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is UK and rural regions for settlement type. Projected shapefile and matrix generated in ArcGIS 9.3.1. environment.

Table 5.10. Spatial regression (ML-SAR) for NMS regions

Model	(46) NMS	(47) NMS	(48) NMS	(49) NMS	(50) NMS
dep. var.: $1/Tln(y_{i,T}/y_{i,t})$					
GDPLEVEL	-0,0055	-0,0051	-0,0049	-0,0078	-0,0085
	(0,0055)	(0,0056)	(0,0055)	(0,0054)	(0,0053)
NATBORDER	-0,0037*	-0,0037*	-0,0035*	-0,0037*	-0,0036**
	(0,0019)	(0,0019)	(0,0019)	(0,0019)	(0,0018)
EUBORDER	-0,0022	-0,0032	-0,0030	-0,0021	-0,0012
	(0,0022)	(0,0022)	(0,0021)	(0,0020)	(0,0020)
INDUSTRY	0,0116**	0,0114**	0,0106**	0,0119**	0,0122**
	(0,0048)	(0,0048)	(0,0048)	(0,0046)	(0,0046)
SERVICES	0,0089	0,0071	0,0059	0,0049	0,0069
	(0,0074)	(0,0075)	(0,0074)	(0,0072)	(0,0071)
CAPITAL	0,0225***	0,0224***	0,0217***	0,0220***	0,0219***
	(0,0034)	(0,0035)	(0,0034)	(0,0034)	(0,0033)
URBAN	0,0068*	0,0065	0,0065		
	(0,0040)	(0,0041)	(0,0040)		
INTERMEDIAT	0,0010	0,0006	0,0007		
	(0,0020)	(0,0020)	(0,0020)		
POPDENSITY				0,0037***	0,0039***
				(0,0012)	(0,0012)
HTEPOPAT	-0,0079**	-0,0087**	-0,0094**	-0,0079**	-0,0071*
	(0,0040)	(0,0040)	(0,0039)	(0,0039)	(0,0039)
NHTEPOPAT	0,0044**	0,0047**	0,0051***	0,0038**	0,0035*
	(0,0019)	(0,0019)	(0,0019)	(0,0019)	(0,0018)
CZ	-0,0234***	-0,0260***	-0,0282***	-0,0252***	-0,0224***
	(0,0046)	(0,0047)	(0,0046)	(0,0046)	(0,0044)
EE	0,0206***	0,0297***	0,0434***	0,0318***	0,0231***
	(0,0071)	(0,0086)	(0,0096)	(0,0082)	(0,0067)
HU	-0,0102***	-0,0104***	-0,0098***	-0,0105***	-0,0103***
	(0,0037)	(0,0037)	(0,0037)	(0,0036)	(0,0035)
LT	0,0070	0,0100*	0,0147***	0,0111**	0,0082*
	(0,0049)	(0,0052)	(0,0053)	(0,0048)	(0,0046)
LV	0,0091	0,0146**	0,0233***	0,0152**	0,0097
	(0,0066)	(0,0073)	(0,0077)	(0,0069)	(0,0062)
PL	-0,0085**	-0,0094**	-0,0094**	-0,0109***	-0,0102***
	(0,0038)	(0,0039)	(0,0038)	(0,0038)	(0,0038)
SI	-0,0099*	-0,0107*	-0,0110*	-0,0090	-0,0082
	(0,0057)	(0,0058)	(0,0057)	(0,0056)	(0,0055)
ρ	0,1764	-0,0475	-0,4041*	-0,0109	0,2056*
	(0,1170)	(0,1767)	(0,2166)	(0,1697)	(0,1116)
W-matrix	$\vartheta : 150km$	$\vartheta : 200km$	$\vartheta : 250km$	$\vartheta : 200km$	$\vartheta : 150km$
LR-test	2,0262	0,0623	3,1547*	0,0034	2,9094
AIC	-769,9170	-767,9530	-771,0460	-775,5010	-778,4070
log likelihood	403,9590	402,9770	404,5230	405,7500	407,2030
N	120	120	120	120	120
R-squared	0,7595	0,7543	0,7625	0,7653	0,7726

Source: own estimations. *Notes:* NMS growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; SAR-maximum likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags insignificant for tested threshold distances ϑ (contiguity, kilometers); constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is SK and rural regions for settlement type. Projected shapefile and matrix generated in ArcGIS 9.3.1. environment.